

Efficient motion analysis and virtual reality methods for preventive and corrective ergonomics

Charles Pontonnier

► To cite this version:

Charles Pontonnier. Efficient motion analysis and virtual reality methods for preventive and corrective ergonomics. Biomechanics [physics.med-ph]. ENS Rennes, 2019. tel-02392255

HAL Id: tel-02392255

<https://hal.archives-ouvertes.fr/tel-02392255>

Submitted on 4 Dec 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Présentée devant :

L'Ecole Normale Supérieure de Rennes

Par :

Charles Pontonnier

Titre :

**Efficient motion analysis and virtual reality
methods for preventive and corrective
ergonomics**

Soutenue le 29 novembre 2019 devant le jury composé de :

Pr. Valentina Camomilla, Bohnes Institute, Rome

Dr. Damien Chablat, CNRS, Nantes

Pr. Laurence Cheze, Université de Lyon 1, Lyon

Pr. Georges Dumont, ENS Rennes, Rennes

Pr. Frédéric Noël, INP, Grenoble

Dr. André Plamondon, Institut de recherche Robert Sauvé en
Santé et Sécurité au travail, Montréal

Pr. Nasser Rezzoug, université de Toulon, Toulon

HABILITATION A DIRIGER DES RECHERCHES

CONTENTS

CURRICULUM VITAE	PAGE 2
------------------	--------

RESEARCH ACTIVITY REPORT	PAGE 14
--------------------------	---------

Chapter 1 – Introduction **Page 15**

Research context.....	16
Research objectives and challenges	18
Document overview.....	21
Main contributions.....	21

Chapter 2 – Efficient musculoskeletal simulation for ergonomics **Page 24**

Introduction	25
Topic 1: Efficient muscle forces estimation.....	28
Topic 2: Efficient scaling	34
Topic 3: Musculoskeletal simulation in industrial conditions	41
Topic 4: Integrative approach	50
Conclusion.....	52

Chapter 3 – Efficient virtual reality for ergonomics **Page 54**

Introduction	55
Topic 1: Biomechanical fidelity of virtual environments	57
Topic 2: Collaborative virtual environments for ergonomics	67
Conclusion.....	74

Chapter 4 – Perspectives **Page 75**

Introduction	76
Evolving industrial work conditions: 4.0 industry	76
Topic 1: Evaluating assistive devices and their impact on workers health	77
Topic 2: Simplifying the evaluation.....	79
Topic 3: Integrating.....	82
Conclusion.....	83

REFERENCES	PAGE 84
------------	---------

CURRICULUM VITAE

CHARLES PONTONNIER

Born on September 24th, 1980 in Sablé sur Sarthe (France)

2 children

EDUCATION

2010 **PhD degree** from the University of Rennes 1, France, def. on Nov. 12, 2010.

“Mechanical simulation for an ergonomic analysis of the workstations: elbow and forearm case”
PhD advisor: Georges Dumont, Professor, Ecole Normale Supérieure de Rennes

Examiners panel: Laurence Chèze (Professor, Lyon University) and Eric Berthon (Professor, Marseille University), Mark De Zee (Associate Professor, Aalborg University (Denmark)), Damien Chablat (CNRS researcher, Nantes), Bruno Arnaldi (Professor, INSA Rennes)

2007 **“Agrégation” (Industrial Sciences – Mechanics)**, secondary teaching qualifications, Ecole Normale Supérieure de Rennes

2004 **Postgraduate degree (Advanced control)**, INSA engineering school, Toulouse, France. Master thesis topic: *“Design and control of an assistive miction robot actuated by artificial muscles”*.

2003 **Engineering Degree (mechanics and control)**, INSA engineer school, Rennes, France

WORK EXPERIENCE & TRAINING

2018 – today Associate professor at ENS RENNES, MimeTIC team. Topic: Musculoskeletal simulation and VR tools for ergonomics
1 year

2012 – 2018 Associate professor at Ecoles de Saint-Cyr Coëtquidan (in secondment of ENS Rennes), MimeTIC team. Topic: Musculoskeletal simulation and VR tools for ergonomics
6 years

2011 – 2012 Temporary assistant professor at ENS RENNES, MimeTIC team. Topic: Biomechanical fidelity of VR environments for ergonomics
1 year

2010 – 2011 Post-doctoral fellowship at Aalborg University, under the supervision of Pascal Madeleine (Professor) and Mark de Zee (Assistant professor). Topic: Musculoskeletal simulation for meat cutting tasks analysis
1 year

2007 – 2010 PhD preparation at the IRISA lab in Rennes, France.
3 years

2005 – 2007 “Agrégation” preparation in Poitiers University and ENS RENNES, France.
2 years

2004 – 2005 Industrial worker, Postman (career break).
1 year

2004 M.Sc preparation at LATTIS (Laboratoire Toulousain de Technologie et d'Ingénierie des
6 months Systèmes), now integrated in LAAS-CNRS lab.

2003 Engineer training at Comau Systèmes France (now, Comau France). Topic:
6 months Characterization and optimization of a robotic car seat assembly process

PUBLICATIONS

JOURNAL PUBLICATIONS

- Pontonnier, C., & Dumont, G. (2009). Inverse dynamics method using optimization techniques for the estimation of muscles forces involved in the elbow motion. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 3(4), 227.
- Pontonnier, C., & Dumont, G. (2010). From motion capture to muscle forces in the human elbow aimed at improving the ergonomics of workstations. *Virtual and Physical prototyping*, 5(3), 113-122.
- Pontonnier, C., Samani, A., Badawi, M., Madeleine, P., & Dumont, G. (2014). Assessing the ability of a vr-based assembly task simulation to evaluate physical risk factors. *IEEE transactions on visualization and computer graphics*, 20(5), 664-674.
- Pontonnier, C., De Zee, M., Samani, A., Dumont, G., & Madeleine, P. (2014). Strengths and limitations of a musculoskeletal model for an analysis of simulated meat cutting tasks. *Applied ergonomics*, 45(3), 592-600.
- Pontonnier, C., Dumont, G., Samani, A., Madeleine, P., & Badawi, M. (2014). Designing and evaluating a workstation in real and virtual environment: toward virtual reality based ergonomic design sessions. *Journal on Multimodal User Interfaces*, 8(2), 199-208.
- Grenier, D., Kerbrat, O., Le Bourhis, F., & Pontonnier, C. (2014). Contribution à la pédagogie par projet : retour d'expérience en conception de systèmes mécatroniques à l'ENS Rennes. *La revue 3EI*, 76, 1-8.
- Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015). Shoulder kinematics and spatial pattern of trapezius electromyographic activity in real and virtual environments. *PLOS one*, 10(3), e0116211.
- Nguyen, H., Pontonnier, C., Hilt, S., Duval, T., & Dumont, G. (2017). VR-based operating modes and metaphors for collaborative ergonomic design of industrial workstations. *Journal on Multimodal User Interfaces*, 11(1), 97-111.
- Muller, A., Pontonnier, C., & Dumont, G. (2017). Uncertainty propagation in multibody human model dynamics. *Multibody System Dynamics*, 40(2), 177-192.
- Cruz Ruiz, A. L., Pontonnier, C., Pronost, N., & Dumont, G. (2017). Muscle-Based Control for Character Animation. *Computer Graphics Forum* 6(6), 122-147.
- Cruz Ruiz, A. L., Pontonnier, C., & Dumont, G. (2017). Low-Dimensional Motor Control Representations in Throwing Motions. *Applied Bionics and Biomechanics*, 1-26.
- Plantard, P., Muller, A., Pontonnier, C., Dumont, G., Shum, H. P., & Multon, F. (2017). Inverse dynamics based on occlusion-resistant Kinect data: Is it usable for ergonomics?. *International Journal of Industrial Ergonomics*, 61, 71-80.

- Cruz Ruiz, A. L., Pontonnier, C., Levy, J., & Dumont, G. (2017). A synergy-based control solution for overactuated characters: Application to throwing. *Computer Animation and Virtual Worlds*, 28(6).
- Muller, A., Pontonnier, C., & Dumont, G. (2018). The MusIC method: a fast and quasi-optimal solution to the muscle forces estimation problem. *Computer methods in biomechanics and biomedical engineering*, 21(2), 149-160.
- Muller, A., Pontonnier, C., & Dumont, G. (2018). MusIC method enhancement by a sensitivity study of its performance: application to a lower limbs musculoskeletal model. *Computer Methods in Biomechanics and Biomedical Engineering*.
- Muller, A., Pontonnier, C., Puchaud P. & Dumont, G. (2019). CusToM: a Matlab toolbox for musculoskeletal simulation. *Journal of Open Source Software* 4.33: 1-3.
- Haering, D., Pontonnier, C., Bideau, N., Nicolas, G., Dumont, G. (2019). Using torque-angle and torque-velocity models to characterize elbow mechanical function: Modelling and applied aspects. *Journal of Biomechanical Engineering*
- Muller, A., Pontonnier, C., & Dumont, G. (2019). Motion-based prediction of hands and feet contact efforts during asymmetric handling tasks. *IEEE Transactions on Biomedical Engineering*.
- Sorel, A., Plantard, P., Bideau, N., & Pontonnier, C. (2019). Studying fencing lunge accuracy and response time in uncertain conditions with an innovative simulator. *PLOS one*.
- Muller, A., Pontonnier, C., Robert-Lachaine, X., Dumont, G. & Plamondon, A. (2019). Motion-based prediction of external forces and moments and back loading during manual material handling tasks. *Applied Ergonomics*.

CONFERENCE PROCEEDINGS (PEER REVIEWED)

- Pontonnier, C., & Dumont, G. (2008). From motion capture to muscle forces in human elbow aiming at improving ergonomics of working stations. In *Virtual Concept 2008 & IDMME 2008* (pp. 8-pages).
- Pontonnier, C., & Dumont, G. (2009). Motion analysis of the arm based on functional anatomy. In *3D Physiological Human Workshop* (pp. 137-149). Springer, Berlin, Heidelberg.
- Pontonnier, C., & Dumont, G. (2010). Functional Anatomy of the Arm for Muscle Forces Estimation. In *Symposium on Computer Methods in Biomechanics and Biomedical Engineering (CMBBE)*.
- Pontonnier, C., & Dumont, G. (2010). Interpolating muscle forces in an inverse dynamics approach. In *Symposium on Computer Methods in Biomechanics and Biomedical Engineering (CMBBE)*.
- Pontonnier, C., De Zee, M., Samani, A., Dumont, G., & Madeleine, P. (2011). Meat cutting tasks analysis using 3D instrumented knife and motion capture. In *15th Nordic-Baltic Conference on Biomedical Engineering and Medical Physics (NBC 2011)* (pp. 144-147). IFMBE Proceedings.
- Pontonnier, C., Dumont, G., de Zee, M., Samani, A., & Madeleine, P. (2012). Cutting force and emg recordings for ergonomics assessment of meat cutting tasks: influence of the workbench height and the cutting direction on muscle activation levels. In *ASME 2012 11th Biennial Conference on Engineering Systems Design and Analysis* (pp. 207-216). American Society of Mechanical Engineers.
- Pontonnier, C., Dumont, G., Samani, A., Madeleine, P., & Badawi, M. (2012). Designing and evaluating a workstation in real and virtual environment: from digital mock-up to realization. In *2012 IEEE 3rd International Conference on Cognitive Infocommunications (CogInfoCom)*, (pp. 249-254).
- Pontonnier, C., Duval, T., & Dumont, G. (2013). Sharing and bridging information in a collaborative virtual environment: application to ergonomics. In *2013 IEEE 4th International Conference on Cognitive Infocommunications (CogInfoCom)*, (pp. 121-126).

- Pontonnier, C., Duval, T., & Dumont, G. (2014). Collaborative virtual environments for ergonomics: Embedding the design engineer role in the loop. In proceedings of IEEE International Workshop on Collaborative Virtual Environments (3DCVE), 2014 (pp. 1-5)
- Nguyen, T. T. H., Duval, T., & Pontonnier, C. (2014). A new direct manipulation technique for immersive 3D virtual environments. In Proceedings of the 24th International Conference on Artificial Reality and Telexistence and the 19th Eurographics Symposium on Virtual Environments (pp. 67-74). Eurographics Association.
- Pontonnier, C., Dumont, G., & Duval, T. (2014). Ergonomics and Virtual Reality: VISIONAIR Project examples. In EuroVR 2014.
- Cruz Ruiz, A. L., Pontonnier, C., & Dumont, G. (2014). A bio-inspired limb controller for avatar animation. Computer methods in biomechanics and biomedical engineering, Proceedings of Congrès de la Société de Biomécanique 2014, 17(sup1), 174-175.
- Cruz Ruiz, A. L., Pontonnier, C., Levy, J., & Dumont, G. (2015). Motion control via muscle synergies: Application to throwing. In Proceedings of the 8th ACM SIGGRAPH Conference on Motion in Games (pp. 65-72).
- Muller, A., Pontonnier, C., Germain, C., & Dumont, G. (2015). Dealing with modularity of multibody models. Computer methods in biomechanics and biomedical engineering, Proceedings of Congrès de la Société de Biomécanique 2015, 18(sup1), 2008-2009.
- Muller, A., Germain, C., Pontonnier, C., & Dumont, G. (2015). A comparative study of 3 body segment inertial parameters scaling rules. Computer methods in biomechanics and biomedical engineering, Proceedings of Congrès de la Société de Biomécanique 2015, 18(sup1), 2010-2011.
- Cruz Ruiz, A. L., Pontonnier, C., Sorel, A., & Dumont, G. (2015). Identifying representative muscle synergies in overhead football throws. Computer methods in biomechanics and biomedical engineering, Proceedings of Congrès de la Société de Biomécanique 2015, 18(sup1), 1918-1919.
- Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015). Kinematic synergy in a real and a virtual simulated assembly task. In Proceedings 19th Triennial Congress of the IEA (Vol. 9, p. 14).
- Muller, A., Germain, C., Pontonnier, C., & Dumont, G. (2016). A simple method to calibrate kinematical invariants: application to overhead throwing. In ISBS-Conference Proceedings Archive (Vol. 33, No. 1).
- Plantard, P., Sorel, A., Bideau, N., & Pontonnier, C. (2017). Motion adaptation in fencing lunges: a pilot study. Computer Methods in Biomechanics and Biomedical Engineering, Proceedings of Congrès de la Société de Biomécanique 2017, 20(sup1), 161-162.
- Haering, D., Pontonnier, C., & Dumont, G. (2017). Which mathematical model best fit the maximal isometric torque-angle relationship of the elbow ?. Computer Methods in Biomechanics and Biomedical Engineering, Proceedings of Congrès de la Société de Biomécanique 2017, 20(sup1), 101-102
- Hilt, S., Pontonnier, C., & Dumont, G. (2017). Model Based Compensation for Low Mass Objects Haptic Manipulation in Virtual Environments. In International Conference on Virtual Reality and Augmented Reality, Lecture Notes in Computer Sciences 10700, (pp. 87-101).
- Muller, A., Haering, D., Pontonnier, C., & Dumont, G. (2017). Non-invasive techniques for musculoskeletal model calibration. In Congrès Français de Mécanique.
- Haering, D., Pontonnier, C., Nicolas, G., Bideau, N., & Dumont, G. (2018). The effects of awkward versus natural shoulder configurations on elbow maximal torque based on isokinetic dynamometer. In XV International Symposium on 3D Analysis of Human Movement.
- Puchaud, P., Sauret, C., Muller, A., Bideau, N., Dumont, G., Pillet, H., & Pontonnier, C. (2018). Evaluation of geometrically calibrated segment lengths: preliminary results on inter-hip, femur and shank cases. In XV International Symposium on 3D Analysis of Human Movement.

- Puchaud, P., Dumont, G., Bideau, N., & Pontonnier, C. (2019). A case study with custom: a comparison of normal and altered gait with an ankle brace. In ESB 2019-25th Congress of the European Society of Biomechanics (pp. 1-1).
- Puchaud, P., Dumont, G., Bideau, N., & Pontonnier, C. (2019). Knee Torque Generation Capacities Modelled with Physiological Torque-Angle-Velocity Relationships. Computer Methods in Biomechanics and Biomedical Engineering, Proceedings of Congrès de la Société de Biomécanique 2019.
- Pontonnier, C., Livet, C., Muller, A., Sorel, A., Dumont, G., Bideau, N. (2019). Ground Reaction Forces and Moments Prediction of Challenging Motions: Fencing Lunges. Computer Methods in Biomechanics and Biomedical Engineering, Proceedings of Congrès de la Société de Biomécanique 2019.

OTHER CONFERENCE PARTICIPATIONS (POSTERS, DEMOS, PRESENTATIONS)

- Pontonnier, C., De Zee, M., Samani, A., Dumont, G., & Madeleine, P. (2011). Trend validation of a musculoskeletal model with a workstation design parameter. ISB Technical Group on Computer Simulation Symposium 2011, Leuven, Belgium, 2011
- Pontonnier, C., & Dumont, G. (2011). Using a Cocontraction Ratio to Predict Antagonistic Behavior During Elbow Motion. International Society of Biomechanics 2011 Congress, Jul 2011, Brussels, Belgium. 2011,
- Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2014). Goal-relevant and non-goal-relevant variability in a real and a virtual simulated assembly task. Book of Proceedings, Isek 2014, Xx Congress of the International Society of Electrophysiology and Kinesiology, 15-18 July 2014, Rome, Italy
- Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2014). Biomechanics of the shoulder joint in real and virtual environments. Book of Proceedings, Isek 2014, Xx Congress of the International Society of Electrophysiology and Kinesiology, 15-18 July 2014, Rome, Italy.
- Nguyen, T. T. H., Duval, T., & Pontonnier, C. (2014). Demonstration of the 7-handle technique. In ICAT-EGVE 2014.
- Pontonnier, C., Villa, C., & Bascou, J. (2016). Identifying knee prosthesis characteristics during swing phase through optimization. In 22nd Congress of the European Society of Biomechanics.
- Haering, D., Pontonnier, C., Bideau, N., Nicolas, G., & Dumont, G. (2016). Preliminary report on the effects of patient positioning and testing modes on elbow isokinetic measurement. In 22nd Congress of the European Society of Biomechanics.
- Muller, A., Pontonnier, C., & Dumont, G. (2016). Uncertainty spreading from kinematics to dynamics in multibody human models. In 22nd Congress of the European Society of Biomechanics.
- Muller, A., Demore, F., Pontonnier, C., & Dumont, G. (2017). MusIC makes the muscles work together. In XVI International Symposium on Computer Simulation in Biomechanics (p. 2).
- Haering, D., Pontonnier, C., Bideau, N., Nicolas, G., & Dumont, G. (2017). Task Specific Maximal Elbow Torque Model For Ergonomic Evaluation. In XXVI Congress of the International Society of Biomechanics.
- Muller, A., Chauwin, M., Pontonnier, C., & Dumont, G. (2017). Influence of Physiological Constraints on a Subject-specific BSIP Calibration. In XXVI Congress of the International Society of Biomechanics.
- Pontonnier, C. (2017) « Applications de la réalité virtuelle en ergonomie » in the workshop « Avancées technologiques pour l'étude des mouvements humains » organized by Julie Côté, Jason Bouffard et Mickael Bégon. 85^{ème} Congrès de l'ACFAS (Montréal)

- Pontonnier C. (2017) « Réalité virtuelle et analyse du mouvement pour la conception et la correction des postes de travail ». Seminar at Institut Robert Sauvé en Santé et Sécurité au Travail (IRSST, Montréal), organized by André Plamondon.
- Puchaud, P., Sauret, C., Muller, A., Bideau, N., Dumont, G., Pillet, H., & Pontonnier, C. (2018). Preliminary comparison of EOS-derived and geometrically calibrated segment lengths: inter-hip and femur cases. In 8th World Congress of Biomechanics
- Muller, A., Pontonnier, C., Robert-Lachaine, X., Dumont, G., Plamondon, A. (2019) Motion-based estimation of back loading during manual material handling tasks, 10th International Scientific Conference on the Prevention of Work-Related Musculoskeletal Disorders (PREMUS 2019)

BOOK CHAPTERS

- Dumont, G., Pontonnier, C., & Wang, Z. (2014). Virtual Reality Based on Interactive Mechanical Simulation for Design Improvement. In Advances in Computers and Information in Engineering Research, Volume 1. ASME Press.

SUPERVISION

POST-DOCTORAL FELLOWS

- Diane Haering, ENVERGO, Joint Torque Envelops for Ergonomics 2015-2017, with Nicolas Bideau and Georges Dumont

PH.D STUDENTS

- Ana Lucia Cruz Ruiz, Ph. D., 2013-2016, co-advisor (50%) with Georges Dumont. “Low-dimensional Control Representations for Muscle-based Characters: Application to Overhead Throwing”, in ENS Rennes DEFENDED
- Antoine Muller, Ph.D., 2014-2017, co-advisor (50%) with Georges Dumont. “Methodologic contributions to the human musculoskeletal analysis for a tradeoff between accuracy and performance”, in ENS Rennes DEFENDED
- Simon Hilt, 2017-, Ph.D., co-advisor (50%) with Georges Dumont. “Biofidelity of haptic interactions for physical risk factor assessments in virtual environments”, in ENS Rennes
- Pierre Puchaud, 2017-, Ph.D., director (100%) and co-advisor (40%) with Georges Dumont and Nicolas Bideau. “Generic and specific musculoskeletal model of the soldier to assist its physical activity”, in ENS Rennes
- Olfa Haj Mamhoud, 2018-, Ph.D., co-advisor (33%) with Franck Multon and Georges Dumont. “Monitoring efficiency and ergonomics on industrial sites”, in Université Rennes 2
- Claire Livet, 2019-, co-director (50%) with Georges Dumont. “Constrained dynamics for musculoskeletal analysis in real time: toward alternative muscle forces estimation methods”, in ENS Rennes

- Louise Demestre, 2019-, co-director (50%) with Georges Dumont, co-advisor (25%) with Nicolas Bideau and Guillaume Nicolas, “Musculoskeletal simulation and elastic structures for sports” in ENS Rennes

MASTER STUDENTS

- Hielke Kiwiet, master student, 6 months internship with Mark De Zee in Aalborg University, 2011
- Stephen Piton, master student, 6 months, with Georges Dumont in Université Rennes 1, 2013
- Antoine Muller, master student, 6 months, with Georges Dumont in ENS Rennes, 2014
- Yuka Ishii, master student, 1 month, in Ecoles de Saint-Cyr Coëtquidan, 2015
- Alexandre Berger, master student, 3 months, in Ecoles de Saint-Cyr Coëtquidan, 2016
- Ryan Abi Sleiman, master student, 6 months, with Diane Haering in ENSAM ParisTech, 2016
- Simon Hilt, master student, 6 months, with Georges Dumont in ENS Rennes, 2017
- Claire Livet, master student, 6 months, with Georges Dumont in Université Rennes 1, 2019
- Thibault Flaven, master student, 6 months in Université Rennes 1, 2019

OTHER SCIENTIFIC ACTIVITIES

REVIEWER

Journals

IEEE Transactions on Visualization and Computer Graphics (TVCG)

Elsevier Applied Ergonomics

Springer Multibody Systems Dynamics

IEEE Computer Graphics and Applications

MDPI Sensors

ACM Computing Surveys

MDPI Computers

Hindawi Complexity

International Journal of Virtual Reality

Conferences

Interfaces Homme-Machine 2015

ACM Virtual Reality Software and Technology (VRST) 2016

IEEE Virtual Reality (VR) 2018

EXPERTISE

Participation to the work group AFNOR on the impact evaluation of body-mounted assistive devices (exoskeletons) on the human at work, led by François Marsy, from September 2015 to March 2017.

Participation to the writing of « accord AFNOR AC Z68-800 » « Dispositifs d'assistance physique à contention de type exosquelettes robotisés ou non - outils et repères méthodologiques pour l'évaluation de l'interaction humain-dispositif » published April 6th ; 2017. Coordinating section « Outils de Simulation ».

PROJECT ID

EUROPEAN FUNDING

VISIONAIR (2011-15)

Call: FP7 INFRA / **Role:** Investigator

Led by Frédéric Noël (Professor, Grenoble INP). The VISIONAIR project was an infrastructure project from call FP7 (GA 262044). The aim was to create a european infrastructure that would be a unique, visible and attractive entry point for high-end visualization and immersion facilities. 20 partners project (6.5 m€). I was involved onto collaborative research activities and transnational access (welcoming european researchers into virtual reality facilities for ergonomic applications).

NATIONAL (ANR) FUNDING

ANR ENTRACTE (2013-16) ~300K€

Call: ANR- CONTINT 2013 Project / **Role:** Local coordinator, Work Package leader

Led by Nicolas Mansard (LAAS-CNRS Researcher, Gepetto Team, Toulouse). The aim of the project was to understand the human motor control in constrained environments to generate control laws for virtual avatars and humanoid robots. Two partners project (LAAS and INRIA). I was coordinator for the INRIA partner and work package leader for « Human Body and Action Models ». ENTRACTE was awarded of the Numerical Grand Prize at the 10th numerics day of the ANR in 2017.

ANR CAPACITIES (2020-24) ~80K€

Call: ANR- PRC 2019 Project / **Role:** Local coordinator, Work Package leader

Led by Christophe Sauret (Institut de Biomécanique Humaine Georges Charpack, ENSAM ParisTech, Paris). The aim of the project is to define biomechanical costs associated to manual wheelchair production. Four partners project (ENSAM, ENS Rennes, CERAH and LAMIH). I am coordinator for the ENS Rennes partner.

OTHER FUNDINGS

INRIA ENVERGO (POST-DOCTORAL FUNDING, 2015-2017), ~90K€

Role: Coordinator

Developing joint torque envelope models for ergonomics.

SAFRAN-SAINT CYR FUNDATION “AUGMENTED SOLDIER IN THE NUMERICAL BATTLEFIELD” INDUSTRIAL CHAIR (DOCTORAL FUNDING, 2017-2020), ~150K€

Role: Musculoskeletal analysis expert

Generic and specific musculoskeletal models for the prototyping of load carriage assistive devices (exoskeletons). Chair sponsored by SAFRAN group, led by Yvon Erhel (Professor, Ecoles de Saint-Cyr Coëtquidan).

RESEARCH SUMMARY

PH.D. PREPARATION AT IRISA (2007-10)

I started my research activity at IRISA in 2007 under the supervision of Georges Dumont. At this date, we were integrated into the Bunraku team, which dealt with motion analysis, avatar animation and virtual reality. Georges did already work on dynamics-based motion analysis/synthesis for humans at this date. As a Ph.D. candidate, my objective was to extend inverse dynamics analysis to the muscle level with a specific focus on performance and accuracy to make it usable in preventive ergonomics (during virtual reality sessions for example). The research key point was to propose innovative approaches in musculoskeletal analysis to diminish the computation time without accuracy loss. My thesis was a real jump into a new world that was the musculoskeletal simulation, and it was the opportunity to propose original ideas around i) advanced cost functions able to better predict co-contraction ii) interpolation-based muscle forces estimation methods able to provide similar results to optimization ones in a significantly lower computation time.

POSTDOCTORAL STAY AT AALBORG UNIVERSITY -SMI (2010-11)

After obtaining my Ph.D. degree I made a 1-year postdoctoral stay in the University of Aalborg, Denmark. This was the opportunity to work with a recognized researcher in the musculoskeletal community -Mark de Zee and a recognized researcher in physical ergonomics – Pascal Madeleine. My topic was to assess the limits of musculoskeletal modeling and the way it can be used for physical risk factors assessment, with a specific application to meat cutting tasks.

I demonstrated the usability of an upper limb musculoskeletal model for physical risk factors assessment, under conditions that are i) relative comparison of work conditions ii) investigating primary task effectors only.

TEMPORARY ASSISTANT PROFESSOR AT ENS RENNES - IRISA (2011-2012)

Back in Rennes after my post-doctoral fellowship, I had a temporary assistant professor position for one year. This short contract was an opportunity for me to join the VISIONAIR project, that was an INFRA FP7 european project, led by Frédéric Noël, enabling the use of Virtual Reality facilities for researchers of various domains. In this scope, I proposed an application to my colleagues from Aalborg, Pascal Madeleine and Afshin Samani to work on the usability of virtual reality for physical risk factors assessment. We developed an ambitious experimental framework, enabling the biomechanical comparison at the postural and muscle level of assembly tasks performed in real and virtual environments. We began to call this biofidelity, or biomechanical fidelity, that is the propensity of virtual environments and their interaction to generate realistic biomechanical responses of the subject regarding a task to perform, a fundamental feature for applications in preventive ergonomics.

We obtained several interesting results, particularly showing that i) there were perception issues between felt and measured postures in VR ii) such simulator was usable as an ergonomic assessment tool since the evolution of most physical risk factors criteria in function of workstation design parameters was similar in real and virtual environments. Obviously, this work was limited to small assembly tasks and need to be extended to a larger applicative scope.

ASSOCIATE PROFESSOR AT ENS RENNES – MIMETIC RESEARCH TEAM (SINCE 2012)

I finally get an associate professor position in mechanics at ENS Rennes, in secondment at Ecoles de Saint-Cyr Coëtquidan (French military school) in 2012. I continued to work in the [MimeTIC research team](#) since this date, continuing to contribute on both virtual reality and motion analysis developments for ergonomics. Since this date, I supervised 7 PhD theses (2 defended, 5 ongoing at this date), 1 post-doctoral fellow and several Master theses.

We particularly focused on the design roles and metaphors to be provided to users in collaborative environments for ergonomics, as well as on efficient motion analysis tools for corrective and preventive ergonomics, with the idea to democratize the use of such tools to non-expert people.

Since September 2018, I achieved my secondment at Ecoles de Saint-Cyr Coëtquidan and I am now at ENS Rennes as an associate professor.

TEACHING SUMMARY

ECOLE DE SAINT-CYR COEQUIDAN (ECOLE SPECIALE MILITAIRE, ECOLE INTERARMES)

- (2012-2018) Numerical methods –20h course (Master 1 mechanics-physics). Design of the course, practicals and writing of the courses supports
- (2012-2018) Simulation of mechanical systems –20h course (Master 1 mechanics-physics). Design and realization of the course, practicals and courses supports with Brice Mudry, Professeur Agrégé in mechanics.
- (2012-2018) Lagrangian mechanics and vibration of discrete systems – 40h course (Master 1 mechanics-physics). Design of the practicals (10h).
- (2012-2018) Numerical control – 20h course (Bachelor 3 electronics). Design of the course, practicals and writing of the courses supports

- (2012-2018) Robotics: serial and legged robots – 20h course (Master 1 electronics). Design of the course, practicals and writing of the courses supports
- (2014-2018) International robotics seminar (international cadets officers) on legged robots – 12h course in english. Design and realization of the course, practicals and courses supports with Brice Mudry, Professeur Agrégé in mechanics.
- (2014-2018) Research projects (100h each, Master 1 mechanics-physics): Design and command of a quadruped robot, Characterization of mechanical properties of knee prosthesis by motion analysis, analysis in ecological situation of amputee gait, design of a rehabilitation system for amputee people. (collaborations with the Centre d'Etude et de Recherche sur l'Appareillage des Handicapés, from « Invalides » institution)

ECOLE NORMALE SUPERIEURE DE RENNES (DEPARTEMENT MECATRONIQUE)

- (2007-2012) Strengths of materials, limitations and specificities – 24h course (Master 2 in higher education of engineering sciences). Design of the course, practicals and writing of the courses supports.
- (2011-2012) Continuum mechanics – 24h course (Master 2 in higher education of engineering sciences). Design of the course, practicals and writing of the courses supports.
- (2014-2019) Mechanical and Multiphysics systems simulation – 24h course (Master 2 in higher education of engineering sciences). Design of the course, practicals and writing of the courses supports.
- (2017-2019) Simulation of poly-articulated systems – 24h course (Master 1 in complex systems engineering). Design of the course, practicals and writing of the courses supports.
- (2017-2019) Serial robotics – 20h course (Bachelor in complex systems engineering). Design of the course, practicals and writing of the courses supports.
- (2007-2019) Preparation to oral exams in « Agrégation de Mécanique » (Master 2 in higher education of engineering sciences). Industrial projects, educational usage of practicals.
- (2017-2019) Numerical methods projects – (Bachelor in complex systems engineering). Numerical methods for human lower limbs simulation, numerical simulation of a transtibial prosthesis.

UNIVERSITE DE RENNES 2

- (2016-2018) Musculoskeletal analysis of workstations ergonomics (Master 1 Engineerig and ergonomics of physical activity).

UNIVERSITE DE RENNES 1

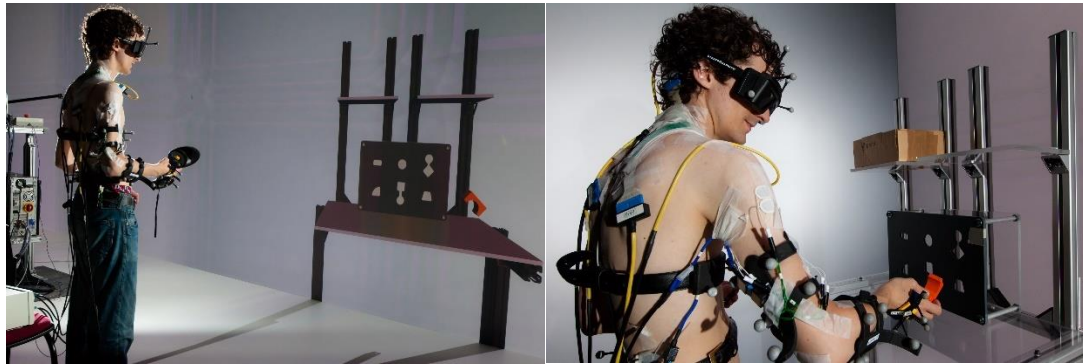
- (2018-2019) Musculoskeletal analysis with CusToM – 8h course (PhD course)

FUN STUFF

Guitarist for 25 years, ukulele player for 13 years, double bass player for 8 years, played in many groups.

RESARCH ACTIVITY REPORT

INTRODUCTION



Simulated assembly tasks in real and virtual environments

Pontonnier, C. et al. (2014). **Assessing the ability of a VR-based assembly task simulation to evaluate physical risk factors**. IEEE transactions on visualization and computer graphics, 20(5)

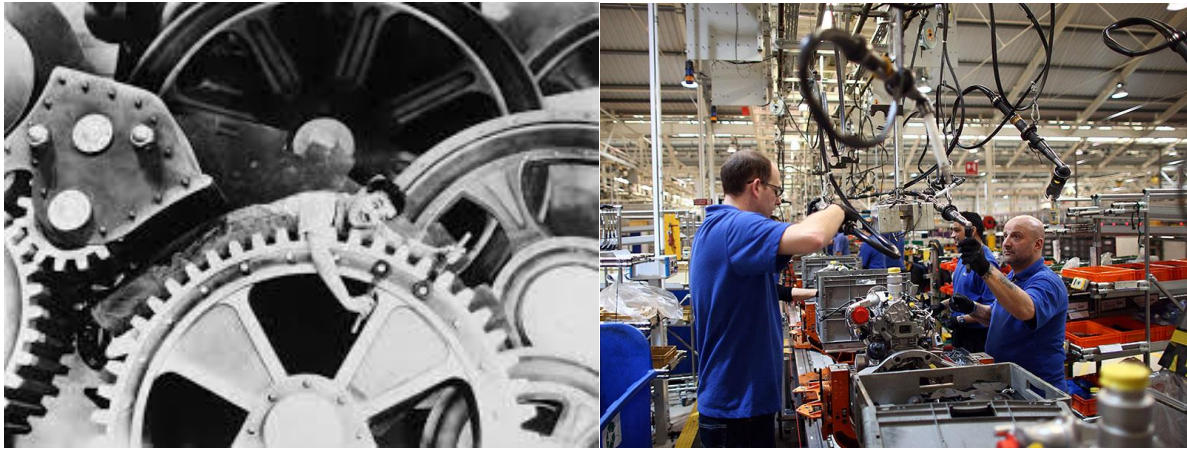


Figure 1.1 – (Left) A scene from Charlie Chaplin’s “Modern Times” illustrating the man-machine interaction and its consequences on the worker health. (Right) An illustrative engine assembly line in 2015 (Getty images).

New manufacturing processes accompanying industrial revolutions impacts work organization as well as work conditions in a broad way. Productive industrial contexts favored the appearance of work-related diseases, especially work-related musculoskeletal disorders (WMSD) that are considered as one of the major health, social and economic issue of the last decades. Annual national and international work reports are all showing similar trends: WMSD declarations are still growing in all countries over the world. WMSD are impacting the health of the worker and its capability to perform his work in a convenient manner. It is in France the 2nd cause of invalidity declaration, being involved in more than 10 million of work days losses in 2015. WMSD represents more than 80% of the work-related diseases to be declared, representing more than 1 million cases in 2017¹. This phenomenon is largely under estimated by the national work-related diseases statistics, since a large part of these diseases are not declared. The 6th European working conditions survey shows that in 2015 back pain (44%), neck and upper limb pains (42%) are the 2 first health issue of European workers (in 28 EU countries plus 5 candidate countries, plus Norway and Switzerland) [1]. WMSD are at first place of the work-related diseases in most industrialized countries.

The risk factors involved in the development of work-related musculoskeletal disorders (WMSD) are commonly divided into internal and external risk factors [2]. Individual factors like age, gender, fitness level, and personality are known as internal risk factors. The external risk factors are expressed in terms of physical and psychosocial components. Stress and pain behavior, as well as work inter-personal relationships have been identified as some of the important psychological risk factors. A relatively fixed erect posture, repetitive arm movements, heavy work, insufficient rest, vibrations as well as static posture are recognized important physical factors contributing to WMSD [2,3]. Thus, the presence of internal and external risk factors emphasizes the complex etiology of WMSD. Further, the inter-relationships among the risk factors do not facilitate the evaluation of the impact of ergonomic interventions.

¹ <https://www.ameli.fr/entreprise/sante-travail/risques/troubles-musculo-squelettiques-tms/tms-consequences>

The need of prevention and occurrence reduction of WMSD is the icing on the cake of all consensual debates about well-being and health at work. However, these intentions are not yet well translated to effective results due to the lack of economic interest for industrials in preserving the health of their employees. This observation tends to evolve in the last ten years due to the demonstrated direct and indirect economical costs for the companies that are caused by WMSD. Since this is a major issue in our modern societies, there is a need of adapted tools and methods to be developed to prevent such diseases systematically in many work sectors, particularly in analyzing the most prevalent risk factors that are the physical ones. Industrial plants are the most obvious playground, since high cadence, strenuous and repetitive tasks are listed as some of the main physical risk factors involved in WMSD appearance. Office work is also a very challenging sector, with prolonged sit posture, neck-shoulder solicitations and carpal syndrome channel occurrences.

To minimize physical risk factors, two types of approaches may be considered:

- **Corrective ergonomics**, that we can define as any corrective action made to minimize risk factors identified on an existing setup. Classically, ergonomists use assessment scores (RULA [4], REBA [5], NIOSH [6] ...) to evaluate the postural and force constraints applied to the worker. These approaches are relevant but asks for long and tedious observation phases to be efficient and can provide information on a restricted set of key moments of the task to be assessed. Therefore, there is a need for low cost and efficient motion analysis tools to be deployed on site to diagnose and help ergonomists to plan an action. Such systems may be efficient only if they can be deployed quickly without perturbing the work process, be easily analyzed by the ergonomist, be fast enough to provide a feedback to the ergonomist or the user in almost real time, and reliable enough to provide insightful information at both postural and force (muscle) levels.
- **Preventive ergonomics**, that we can define as any preventive action made to minimize risk factors during the design of a work setup. Such approaches were historically applied to physical mock-ups on which the methods evoked above for corrective ergonomics were applied. A physical mock-up is not easy and fast to realize and is quite complex to modify in order to minimize a risk factor. Digital mock-ups opened the way to several enhancements in preventive ergonomics. First, digital manikins were used to assess risk factors on a mock-up only by simulation – what is commonly called digital human modeling [7]. This approach is limited since it does not consider the worker specificities (morphology, work habits, skills...) and is mainly postural (therefore applied to reachability issues or key moments of the task), even if several advances have been made on physically realistic manikins [8] and on incorporating force features in the assessment [71]. Therefore, there is a need for low cost and efficient tools to be used during the design phase of a workstation and involving the worker in the design and assessment. Such systems may be efficient only if they are able to properly represent the real work conditions (leading to similar biomechanical solicitations), to make user and experts able to participate to the design, to make the design easy to modify, and to make the results available quickly.

Both approaches can be extended to any other risk factor mentioned above, even if it is not the purpose of the current document. Their application to the physical risks factors is leading to several research questions that are presented below and that are the main scientific objectives of my research.

RESEARCH OBJECTIVES AND CHALLENGES

The approaches presented above are leading to a set of scientific challenges to be reached. In the following sections, we are presenting a brief introduction of these challenges.

DEMOCRATIZE MUSCULOSKELETAL SIMULATION AS A DAILY LIFE TOOL FOR ERGONOMISTS

Both preventive and corrective approaches ask for efficient motion analysis tools to be deployed and integrated as support decision for ergonomists. Musculoskeletal simulation is the most advanced way to analyze motion and the most relevant simulation to be used in ergonomics, for the following reasons.

The interests and applications for musculoskeletal simulation (MS) are on the rise in diverse fields in addition to ergonomics, e.g. rehabilitation sports, clinics... Indeed, this tool has the potential to provide insightful information about motion and motor control of humans at kinematical, dynamical and muscle levels through minimally invasive measurements.

The simulation itself consists in solving kinematics and dynamics equations of a motion in order to estimate the forces necessary to generate it. Classical musculoskeletal simulation is performed in a “inverse dynamics” fashion way, leading to the following analysis pipeline:

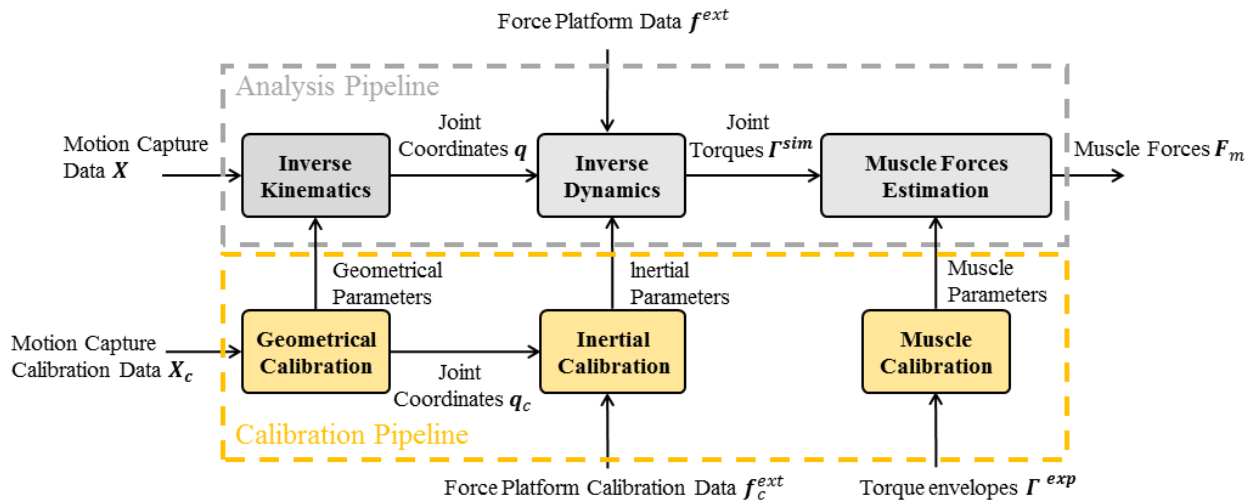


Figure 1.2. Classical inverse dynamics musculoskeletal simulation pipeline. Inputs are generally motion capture data and external forces measures data, and outputs are the quantities on the right side of the boxes: joint coordinates, joint torques and muscles forces against time. Joint reaction forces are also one of the possible outputs depending on the way the inverse dynamics step is implemented. Calibration procedures accompany these analysis steps to scale the corresponding layers of the musculoskeletal model (geometrical, inertial and muscle layers) to the subject. Extracted from [9].

Generally, in MS, a musculoskeletal model (MSM) relies on an arborescent structure of rigid segments linked by joints and actuated through muscles. Therefore, such a model exhibits 3 descriptive levels of parameters coupled together. First, the geometrical level (segment lengths, joint centers ...) corresponding to the osteo-articular model, second, the inertial level (mass, inertias, center of mass...), and last the muscle level. The last one mixes geometrical parameters that may be issued from the first one (muscle chiefs' origins/insertions, via

points, wrapping surfaces...) and force generation parameters (Maximal isometric strength, tendon slack length ...). This hierarchy is leading to a large set of parameters influencing such simulation.

Three major leaks remain to achieve widespread use of such inverse analysis in ergonomics:

- First, computation methods must be enhanced to make these simulations easier to deploy and use daily, with a higher accuracy in the results. Currently, most musculoskeletal analyses need heavy pre-processing of the data, large computation time and heavy post-processing to give relevant results. This is clearly non-compatible with a daily use by non-expert users such as ergonomists, asking for a similar level of accuracy with drastically decreased computation and processing times. This is also a real need to make such simulations usable in preventive ergonomics sessions, leading to similar computation issues. Reducing computation time also opens the opportunity to enhance the work conditions by biofeedback, enabling the worker to assess and modify by itself its work gestures and procedures. There are also efforts to be made on the force estimation problem itself, representing more accurately the motor control of the subject in relation to a task. It is well known that current methods used in the field badly predict co-activation behaviours for example.
- Second, the calibration of MSM to subjects (scaled to subject models) still requires significant improvements to be made. Now, accurate models are systematically based on invasive, expensive and rare tools (MRI, CT-scans, ...). Moreover, this data asks for tedious post-processing to be used for scaling. There is a need of simplified scaling methods able to personalize models in a limited time and with a limited set of measures, as it would be used in an ergonomics context.
- Third, the experimental facilities necessary to drive such simulation are still heavy to deploy and costly (optoelectronic systems, force platforms...). This is also non-compatible with onsite analysis. In an industrial plant, a complete motion capture system with external force measurements is difficult to deploy and ask to modify the environment (occlusions, luminosity) to be efficient. This reduces the ecology of the situations to analyse and impact the production of the plant. There is a need of methods able to provide accurate musculoskeletal results from a degraded or reduced set of data, collected with limited and minimally impacting equipment.

These issues are motivating most of the developments I present in the second chapter of this manuscript, and are extensively described there.

MAKE VIRTUAL REALITY REALISTIC AND USABLE ENOUGH TO BE USED IN PREVENTIVE ERGONOMICS

The recent development of virtual reality headsets and glasses made it very popular the last few years. This is also a valuable tool to prototype virtually workstations and products. This approach is more cost-effective and convenient since working directly on the Digital Mock-Up (DMU) in a virtual environment is preferable to constructing a real physical mock-up in a Real Environment (RE). This is substantiated by the fact that a Virtual Reality (VR) set-up can be easily modified, enabling quick adjustments of the workstation design. Indeed, the aim of integrating ergonomics evaluation tools in VE is to facilitate the design process, enhance the design efficiency, and reduce the costs. VR has already been used in ergonomics to assess aspects of manual handling operations [10,11,12]. In such applications, the end-user, generally the future operator of the workstation to design, is immersed in a VR-based simulator that mimics the real work environment and he or she is asked to perform tasks through interactions in VE corresponding to tasks he would perform in RE. Interactions are mostly performed with peripherals such as motion-tracking systems or haptic interfaces. Other actors of the

design - ergonomists, in charge of the evaluation of the system regarding the user, and design engineers, in charge of the functionality of the system regarding the production scheme – can also interact with the scenes and the end-user to enhance both working conditions and workstation usability. Generalize the use of such systems to systematize the ergonomic assessment in a design process ask for the following research questions:

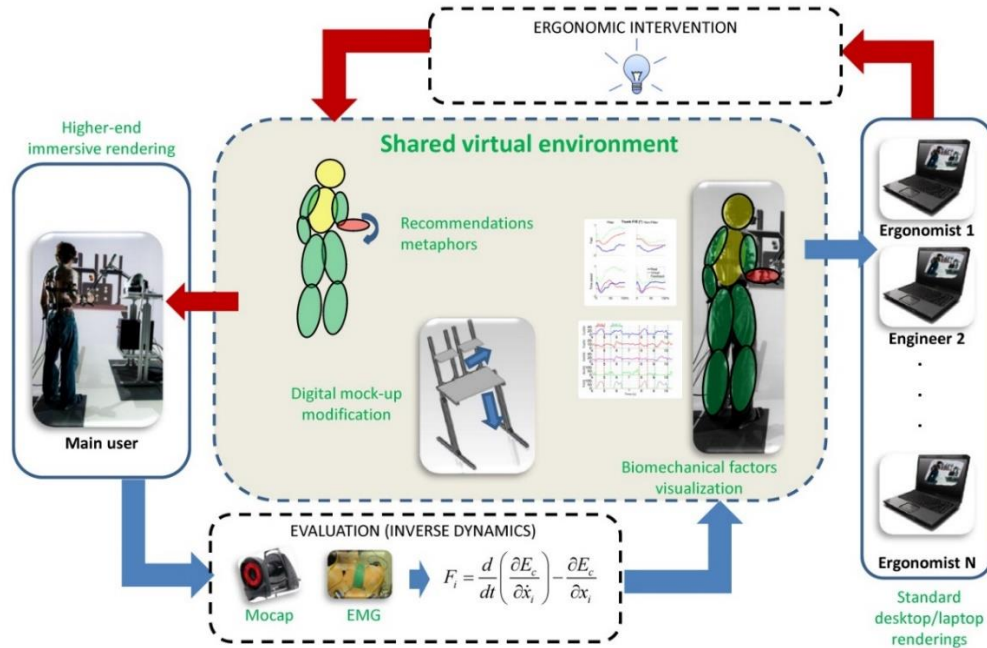


Figure 1.3 –A generic collaborative framework for ergonomics assessment in a virtual environment, involving an end-user (operator), ergonomists and design engineers (from [13]).

- First, the environment must be collaborative and propose efficient metaphors and design modes to be used by the different actors of the design. It asks for architectural and behavioral questions, regarding the way the actors are interacting with the scene and between them. For example, an ergonomist must be able to provide ergonomic recommendations to the end-user and the design engineer whereas the latter may have to indicate production constraints to the other actors.
- Second, how reliable are the recommendations issued from a VR-based ergonomics study? And how realistic is the simulator? To make a VR simulator usable for ergonomics purposes, it asks to ensure the transferability of the results from the virtual world to the real one. This transferability can be reached only at a cost of the thorough assessment of the realism of the simulator regarding the tasks to simulate.

Therefore, there is a need of collaborative methods in high end realistic environments to democratize preventive ergonomics as a credible decision support tool for ergonomists and designers, and a real need of assessment of the realism of such systems in biomechanical terms to be used in preventive ergonomics.

APPLIED AND AFFORDABLE

There is no interest in having such applied research objectives if there is no application behind. It is fundamental to me that the developments we make in the two domains presented above must be applied to real cases. Musculoskeletal simulation as well as VR are generally still used by experts without a real adoption of the methods by end-users (ergonomists in our case). To achieve a deployment of such methods in broad way, there is a need of tools to be developed that would be i) easy to use ii) fast and integrative iii) customizable.

There is also a lot to do to prove the interest and usability of such methods in many applicative fields. Therefore, all the applications we can pursue are of interest to show the usability of these methods in these cases.

DOCUMENT OVERVIEW

Regarding the challenges presented above, the next chapters are explaining into details the different contributions I participated to in the last 12 years, since I began my PhD thesis. A final section is concluding and opening perspectives to this work. The figure 1.4. summarizes the principle of corrective and preventive assessment of physical risk factors and replace the plan of the manuscript within this scheme.

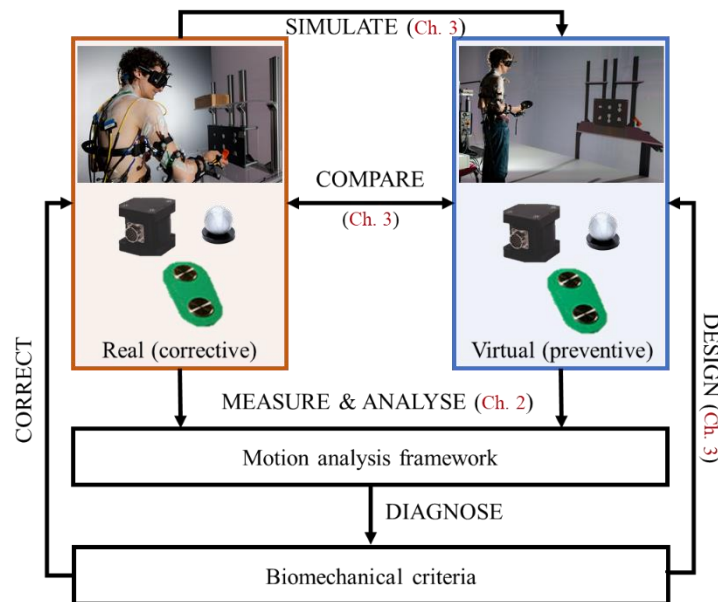


Figure 1.4. Document overview: corrective and preventive physical risk factors assessment and the corresponding contributions gathered by chapters.

The scientific contributions related to the challenges are summarized in the following section.

MAIN CONTRIBUTIONS

EFFICIENT MUSCULOSKELETAL SIMULATION FOR ERGONOMICS (CHAPTER 2)

As stated in introduction, musculoskeletal simulation is a fundamental tool for studying physical risk factors at work. To enhance their efficiency and reliability, we proposed several contributions related to the issues raised in the previous section.

EFFICIENT MUSCLE FORCES ESTIMATION

In this contribution we proposed alternative methods (interpolation) to classical (optimization) methods for muscle forces estimation. The main strength of this approach consists in its propensity to get in a very reduced time, compared to classical methods, results with a similar optimality. The developed method (MusIC, for Muscle Forces Interpolation and Correction) is about 30 times faster than classical optimization for a 12 DoF lower limbs model with 82 muscles.

EFFICIENT SCALING

Musculoskeletal models have to be scaled to the subject in order to be as accurate as possible. We proposed several studies on this subject to get i) realistic geometrical parameters (segment lengths, joint axes...) ii) realistic muscle parameters (maximal isometric force, optimal muscle length...). We particularly explored the importance of these parameters with regard to the results through sensitivity studies. We also proposed alternative joint strength models to represent the subject capacities in terms of force generation, that is absolutely fundamental for physical risk factors assessment.

MUSCULOSKELETAL SIMULATION IN INDUSTRIAL CONDITIONS

Such simulations are interesting only if they are applicable to real situations. Therefore, we developed methods to make it usable out of the lab. We particularly developed inverse dynamics methods based on depth camera data, since this device is easy to deploy in any environment with a minimal action on the subject to study, and we developed external forces prediction methods able to provide external forces applied on a given subject from a measure of its motion only. Such method is really relevant out of the lab, since force platforms or any over external forces measurement device are difficult to deploy on field.

INTEGRATIVE APPROACH

All of our development in musculoskeletal simulation have been integrated in a single open source Matlab toolbox², following the idea that: i) it has to be usable by anyone ii) it has to be as modular as possible (changing

² <https://github.com/anmuller/CusToM>

models, analysis to run, input data ...) iii) it has to be alive. I am particularly proud to have participated to this development, that is full of promises for the next years.

EFFICIENT VIRTUAL REALITY FOR ERGONOMICS (CHAPTER 3)

As I already explained above, virtual reality is a powerful and appealing tool for preventive ergonomics and physical risk factors assessment. To enhance its efficiency and reliability, I proposed several contributions relative to the issues raised in introduction.

BIOMECHANICAL FIDELITY OF VIRTUAL ENVIRONMENTS

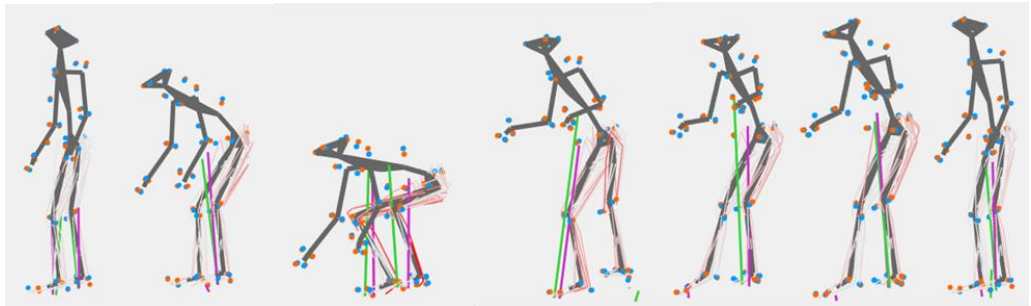
First, we made some fundamental studies comparing real and virtual assembly/sorting tasks in terms of biomechanical quantities. These works showed interesting similarities and discrepancies between real and virtual results, enabling a cautious use of such setup for preventive ergonomics...of such tasks. It led us to the concept of biomechanical fidelity, that is extensively presented in the introduction of the corresponding chapter.

COLLABORATIVE VIRTUAL ENVIRONMENTS FOR ERGONOMICS

Second, we focused on collaborative virtual environments, enabling the joint work of 3 actors, that are an ergonomist, a design engineer and an end-user. We particularly focused on the interaction modes and metaphors that such setups may propose, and on their evaluation in terms of usability.

E

fficient musculoskeletal simulation for ergonomics



Motion analysis of a handling task with the CusToM toolbox

Muller, A. et al. (2019). **CusToM: a Matlab toolbox for musculoskeletal simulation**. Journal of Open Source Software.

INTRODUCTION

Developing efficient musculoskeletal simulation for ergonomics is a real need regarding the specificities of this activity. Indeed, preventive or corrective ergonomics in an industrial context are subject to constraints, having to be performed in a limited time and with limited means. At the same time, having an idea of forces exerted by the worker is mandatory to have a complete assessment of its work conditions. This observation militates for tools that can be accurate enough to provide reliable force information about the workers activity, fast enough to be deployed in a relatively short time and deployed with a minimum of experimental means. Several commercial or open-source musculoskeletal simulation solutions have been developed during the past years. The two most well-known software solutions are the AnyBody Modeling System [14] and OpenSim [15]. Such systems have found multiple applications in clinics, sports, rehabilitation as well as exoskeleton prototyping. Their use in physical risk factors assesement is still subject to questions, that I will now develop.

The musculoskeletal analysis of a motion by inverse dynamics thanks to a musculoskeletal model exhibiting n_c degrees of freedom, n_b bodies, and n_m muscles can be summarized by the following scheme:

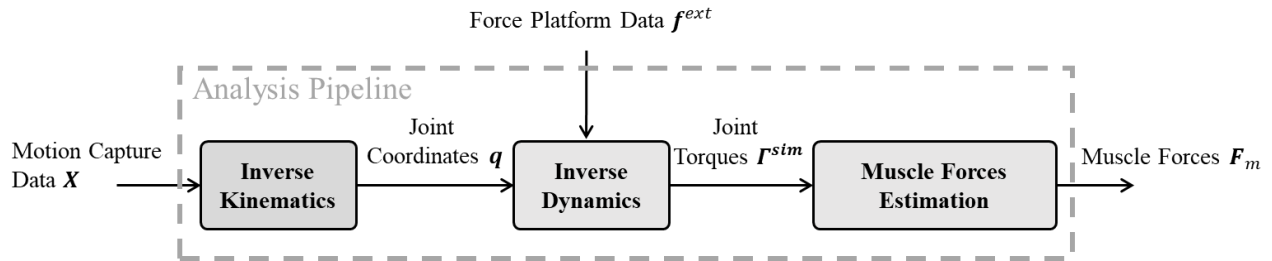


Figure 2.1. Inverse dynamics analysis pipeline.

Generally, the inputs are motion capture data coming from an optoelectronic system, in other words the 3D position against time of a set of markers \mathbf{X} , and external forces data coming from force platforms, in other words 6D efforts (forces and moments) under each foot of the subject \mathbf{f}^{ext} . The first processing step (inverse kinematics) consists in computing the joint coordinates and its derivatives against time $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$. This is generally done by minimizing the distance between experimental and reconstructed markers placed on the kinematical model, that can be defined as an optimization problem [16], although alternative methods proved their value to compute the joint coordinates efficiently (Jacobian-based [9], Extended Kalman filters [17]). The second step consists in the inverse dynamics itself, generally solved thanks to an iterative approach like the Newton-Euler algorithm if the biomechanical model is an open structure, or global (Lagrange based) approaches for structures involving closed loops [18]. Therefore, it computes the joint torques $\mathbf{\Gamma}^{sim}$ from the external forces and the motion quantities in the joint space $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$. Finally, the muscle forces estimation is the step computing the muscle forces from the joint torques. Most musculoskeletal models exhibit actuation redundancy that leads to an infinite number of actuation solutions, as there are less equations (dynamics equations) than unknowns (muscle forces, given that muscles can only pull). The models may also exhibit under actuation, due to the fact that a single muscle can actuate several joints simultaneously, such as bi-articular muscles. These challenges can be solved by defining what is the optimal actuation solution, through the modelling of known motor control laws associated to a motion. Several models of motor control are actively studied and used in the fields of neuroscience, biomechanics, and robotics to generate muscle forces. In inverse dynamics based musculoskeletal analyses, the force sharing problem – distributing the forces deployed by muscles to generate a given motion – is mostly solved thanks to optimization methods. In [19, 20] the force sharing problem is assumed to be an optimization problem, consisting in minimizing a criterion representing a central nervous system (CNS) strategy. The criterion represents a cost, e.g. metabolic energy, muscle fatigue or joint reaction forces. It is also

noteworthy that both inverse dynamics and muscle forces estimation must be solved simultaneously in the case of closed loop systems, since computing the joint torques for closed-loop is a non-sense. This is the way it is handled in AnyBody for example [14].

The analysis pipeline applies inputs to a model that needs to be scaled to the subject to study. A classical whole-body musculoskeletal model exhibits ~ 50 DoF, ~ 50 solids, and ~ 300 muscles that leads to ~ 5000 parameters to be known to fully scale it. At the geometrical level, the parameters are segment lengths, joint axes, joint locations and muscle paths. At the inertial level, the parameters are the body segments inertial parameters (masses, centers of masses locations, inertia matrices). At the muscle level, the parameters are the force generation parameters (optimal muscle fiber length, maximal isometric force...). Individual factors such as height, weight, or fat mass index are completing this model and may be used to scale it [21].

Classically, regression methods based on anthropometric data collections on cadavers have been used to scale both geometric and inertial parameters [22,23,24]. Muscle parameters have also been scaled thanks to anthropometric rules, as it has been done in [25] or presented in [26]. However, such methods do not enable to obtain accurate subject specific models. Three-dimensional scanning or magnetic resonance imaging measurements have also been used to calibrate precisely and individually geometric, inertial and muscle parameters [27,28,29], but these methods are expensive, long to post-process and can be invasive (radiations). Consequently, subject-specific scaling methods with lighter, less invasive and faster protocols have been developed. These methods mainly rely on equipments available in a motion analysis laboratory.

Calibration of geometrical parameters (joint axes orientations, bone lengths, joint positions...) based on motion capture data has been proposed in several studies [30-33]. In most of these papers, the main idea consists in minimizing the reconstruction error between the model anatomical landmarks location and recorded experimental markers placed on the same landmarks among a given set of frames. Segments dimensions and joint centers of rotation are then extracted from the optimized data. Solutions [32,33] are the ones implemented in the AnyBody Modeling System, whereas solution [31] can be found in OpenSim.

Non-invasive optimization methods have also been proposed to estimate personalized inertial parameters (center of mass location, mass, inertia...) in vivo. It requires using motion capture and external force measurements to obtain the optimal Body Segment Inertial Parameters (BSIP) that best fit the motion dynamics equations [34]. Different approaches were used to solve this problem. [35, 36,37] wrote the inverse dynamics to inertial parameters relationship under the form of a system of a linear equation and solve the corresponding problem in a least-square sense. This approach has also been applied to more affordable measurement systems [38]. Meanwhile, [39,40] focused on the 6 degrees of freedom (DoF) joint between the floating-base system and the global reference frame as a measure of the simulation accuracy. The optimization problem consisted in minimizing the generalized forces at this virtual joint that corresponds to the dynamic residuals. We can also cite [41] that estimated the inertial parameters by adjusting ellipsoid shapes on photographs and anatomical landmarks from motion capture data. The AnyBody modeling system does not have any inertial calibration (customized values are scaled from geometrical parameters and initial anthropometric values), whereas OpenSim uses a residual reduction algorithm (RRA) to modify masses and centres of mass position, by minimizing the residuals between external forces and acceleration data (a method close to the ones proposed in [39,40]).

Finally, the most challenging calibration remains on the muscle aspect, since no direct measurement of muscle force generation parameters is possible and only a few non-invasive (strength based) techniques exist [42]. We will separate the muscular calibration in two steps. First, the geometrical calibration described above is also used to scale the relative origin, insertion and paths of the action lines of muscles. Next, the muscular calibration itself is calibrating the muscle force generation parameters (tendon slack length, isometric strength...). These techniques are based on the measurement of the maximal joint strength (i.e. the maximal torque developed by a given joint for a given angular position and velocity, thanks to an isokinetic ergometer) corresponding to isometric or isokinetic muscle efforts and trying optimizing muscle parameters to match these values. For example, [43] proposed a two-step optimization method based on isometric measurements, first solving the

force sharing problem among upper limb joints, and second fitting at best individual muscle torques by changing muscle parameters. [44] proposed a similar approach with the addition of isokinetic trials to enhance the calibration whereas [45] used isometric trials and EMG to scale muscles parameters of a hand MSM. [46] proposed an approach coupling EMG measurements and motion capture trials to calibrate the musculo-tendon parameters of the muscles crossing the elbow [45] has been applied with a low coupling with the AnyBody modelling system whereas OpenSim only exhibits a geometrical calibration. Force generation parameters are not scaled to the subject in this software. In a general way, there is no whole-body rule enabling a complete scaling from a set of measures for this layer of the MSM.

Even if this short summary of what we call musculoskeletal simulation is appealing for ergonomics, there are still several limitations hampering its use, as we already presented it in the introduction of this manuscript:

- First, computation times must be decreased in order to make these simulations easier to deploy and use daily. Optimization remains costly in terms of computation time, despite of several implementations and improvements in the last years. Mostly, the use of Sequential Quadratic Programming Methods (SQP) have deeply improved the computation times since the muscle forces estimation problem is well shaped for such an algorithm. However, in real-time simulations including muscle forces estimation, the result remains suboptimal. In the method proposed in [47], muscles were gathered by functional groups to reduce the problem complexity, that led to strong bias in the estimated forces. In the work of [48], the use of a neural network dedicated to quadratic optimization led to a real-time but sub-optimal result, since computation time was limited to ensure real-time computation. Moreover, force-length and force-velocity relationships were not considered in the muscle models in this paper. Last, these approaches are limited to a given musculoskeletal model and are not systematically applicable to any other model. Therefore, there is a need for alternative methods able to give in a limited amount of time similar results to classical methods and independent from the model to be analysed. This is one of the contributions I work on during the past twelve years, as it is presented in the following section.
- Second, the calibration of MSM to subjects (scaled to subject models) may benefit for simplification in both acquisition and processing of the data, to bypass too invasive and costly methods - imagery based methods. Even if alternatives methods circumvented these issues by using directly the motion and external forces data to scale the subject as mentioned above, there is a lack of validation of these methods. Since they indirectly calibrate the parameters with resulting values (motion, forces,...), they have a propensity to overfitting, meaning over-calibrating parameters to minimize an error that is caused by another issue. Moreover, their usefulness is questioning and may ask for sensitivity analyses to understand their importance in the accuracy of the results. The second topic of this chapter deals with these analyses and their impact on these methods.
- Third, the data acquisition and processing should be simplified drastically to make it usable onsite. In an industrial context, there is no room for heavy and impacting protocols. The systematic use of optoelectronic motion capture data and force platforms for such analyses is particularly constraining. A few studies showed the potential application of inverse kinematics and inverse dynamics methods to alternative motion capture data, such as inertial measurements units (IMUs) [49-52] and Depth cameras [53] data. If IMUs data tend to be as accurate as motion capture, the scaling of the model is still very complicated with such a system since it provides no absolute measure of distance. Moreover, the application of classical inverse dynamics methods remains a complex procedure with such a data. Depth cameras showed a good potential to be used in ergonomics, however the input data is relatively poor and ask for simplified models to be deployed (ex: no wrist motion, no ankle motion) for inverse dynamics analyses. Finally, these analyses are very limited by the lack of external forces measurement. This data is mandatory to estimate internal forces and torques. A few studies proposed approaches to estimate these forces only from the whole motion of the subject, but there is still a need of improvement

to make them usable with any model and with multiple contacts. These issues are leading to the third topic of this chapter.

- Last, to democratize the use of this tool for physical risk factors assessment, there is a necessity of simplification of the processing to make it usable by non-expert people. Currently, musculoskeletal simulation still asks for expertise to be driven (typically: researchers of the domain), and tedious pre and post-processing actions. The definition of new models to be studied and coupled with original analysis protocols asks for complex developments in softwares like OpenSim or AnyBody. This issue is leading directly the contribution proposed in the fourth topic of this chapter.

TOPIC 1: EFFICIENT MUSCLE FORCES ESTIMATION

CONTEXT AND OBJECTIVE

In relation to the first issue presented in the previous section, we focused on the development of muscle forces estimation methods that could run in -almost- real time, independently from the model to run and independently from the problem to solve. In other words, we proposed solutions able to replicate the results of an optimization method without solving it. The main assumption behind this kind of solution is that we can find from pre-computed data an approximation of the optimal solution, since muscles are viscoelastic actuators that behave continuously against time (and therefore against motion quantities) due to their force-length and force-velocity relationships. The first occurrence of this idea was developed during my PhD thesis [54,55]. This first approach consisted in approximating the solution of a classical optimization thanks to a barycentric interpolation in the articular space $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$. First, it consisted in feeding a database with results of a classical optimization. For a set of reference motion capture and external forces data, we computed the following optimization:

$$\left\{ \begin{array}{l} \text{At each frame :} \\ \min f(\mathbf{F}) = \sum_{n_m} \left(\frac{F_i}{F_{max_i}} \right)^2 \\ \text{Subject to:} \\ \boldsymbol{\Gamma}^{stim} - \mathbf{R}\mathbf{F} = \mathbf{0} \\ F_i - F_{max_i} \leq 0 \end{array} \right. \quad (1)$$

Where \mathbf{F} is the muscle forces vector - \mathbf{F}_{max} being the maximal muscle forces vector, $f(\mathbf{F})$ the cost function to minimize - representing the CNS behavior (here the squared sum of the normalized muscle forces), $\boldsymbol{\Gamma}^{stim}$ the joint torque vector and \mathbf{R} the moment arms matrix. The database was transformed through a Delaunay tessellation of the $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ joint space.

The interpolation step consisted, for a sample motion, to find at any frame the simplex containing the current $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ state of the joint and to apply a barycentric interpolation to the current state inside this simplex to find an approximation of the muscle forces, as shown in figure 2.2.

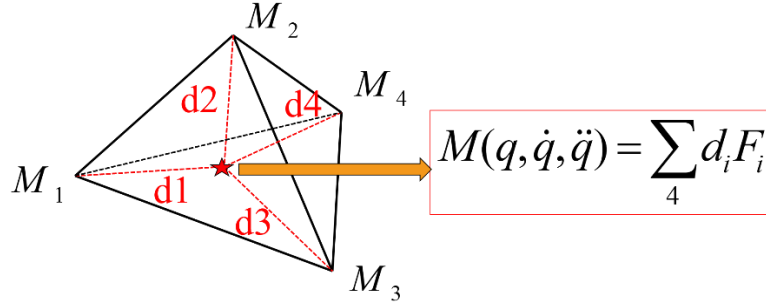


Figure 2.2. Barycentric interpolation of muscle forces in the joint space.

This approach has shown promising results, especially in terms of computation time and a real portability between subjects. However, there were large concerns about the extension of such a method to multibody models and multi-articular muscles, mostly due to the high degree of coupling existing between joints. Moreover, the method did not ensure the dynamical equilibrium of the interpolated forces, that led to unrealistic force sharing solutions with respect to the mechanics of the motion.

This very first approach led us to the developments that are presented in the following section. This work has been particularly developed during the Ph.D of Antoine Muller, who I happily supervised with Georges Dumont between 2014 and 2017.

THE MUSIC METHOD

The limitations of the barycentric interpolation led us to develop the MusIC method, meaning Muscle forces Interpolation and Correction [56]. We based this approach on two main hypotheses:

- the muscle forces problem can be first solved joint per joint and the inter-joint muscular coupling (multi-articular muscles) can be taken into account a posteriori;
- the muscle forces can be corrected to respect the dynamic equilibrium.

Therefore, the MusIC method is separated in two steps. The first one consists in computing a database describing the muscle forces sharing solution joint per joint. The second one consists in interpolating forces thanks to this database, mixing them to consider muscular coupling and finally correcting them to respect the dynamics of the motion.

The database generation and structure are explained in figure 2.3. It consists, as in the first approach described in the previous section, in storing the muscle forces sharing solution joint per joint. The difference here is that there is no need of experimental data to compute the solution: the articular space is discretized, and a solution is found for all the configurations of a given joint by applying an arbitrary positive or negative joint torque to the joint. The solution for the given joint (primary) and the ones impacted by pluri-articular muscles crossing this joint (secondary) is obtained by solving the following equation:

$$\left\{ \begin{array}{l} \text{At each frame :} \\ \min f(\tilde{\mathbf{F}}) \\ \text{Subject to:} \\ \mathbf{\Gamma}^{sim} - \tilde{\mathbf{R}}\tilde{\mathbf{F}} = 0 \\ F_i - F_{max_i} \leq 0 \end{array} \right. \quad (2)$$

Where \sim refers to the joints (primary and secondary) affecting the moment arms of the joint associated to this sub-database and muscles actuating this joint. Thus, $\tilde{\mathbf{R}}$ is the sub-matrix of \mathbf{R} containing the rows associated to the referred joints and the columns associated to the referred muscles. $\tilde{\mathbf{F}}$ is the sub-vector of \mathbf{F} containing the forces associated to the referred muscles. $\mathbf{\Gamma}^{sim}$ contains the torques applied in referred joints $-\Gamma^{sim}$ for the joint associated to the sub-database and zero value for the others. A vector of normalized activations – activation ratio vector α is then stored for the considered configuration. f is the cost function the method will emulate.

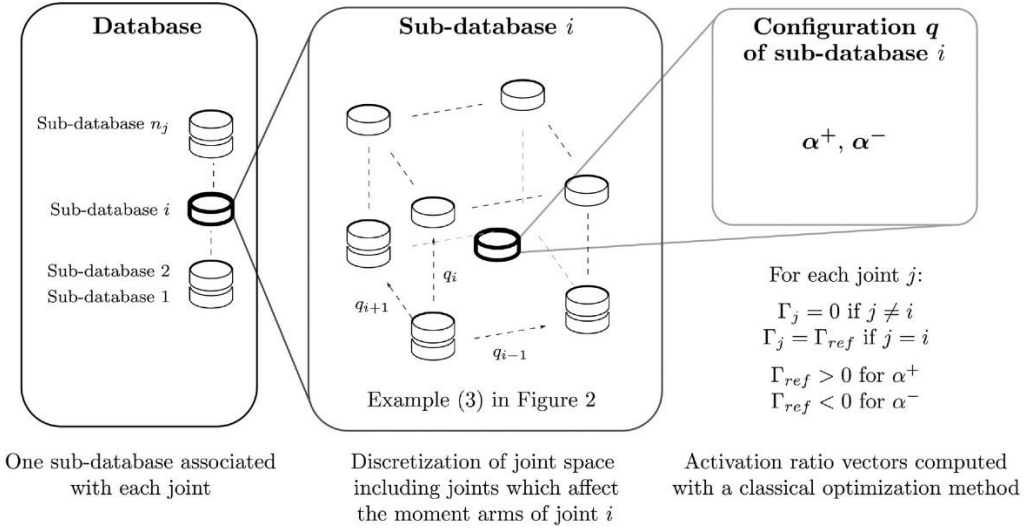


Figure 2.3. Database structure for activation ratios vectors α for a given joint i . Activation ratios are normalized with the sum of the activations of the considered joint to make them independent from the joint torque.

Once the database compiled, the method can be applied to sample motions. As shown in figure 2.4., the interpolation step consists, for a given frame, to find the closest configuration in each joint sub-database and to compute a set of muscle forces for the muscles crossing this joint, by multiplying the activation ratio vector α by the joint torque value relative to the moment arms of the muscles crossing the considered joint. This interpolation leads to multiple force values for pluri-articular muscles. Considering the joint torque to be generated joint per joint, a barycentric interpolation between these values is computed to obtain a single muscle force vector for all the muscles of the model at the considered frame. Finally, to ensure that the solution is physiologically realistic and respects the dynamics of the motion, a correction is computed. It consists in finding the closest solution to the interpolated forces of the previous step subject to the dynamic equilibrium and the physiological properties – muscles can only pull with maximal forces. An active set method using Karush-Kuhn-Tucker (KKT) conditions is used to solve this problem. The gradients are analytically computed since the cost function is quadratic and constraint equations are linear.

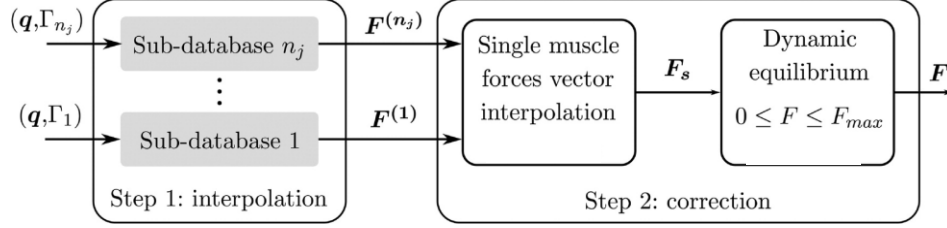


Figure 2.4. Step 2 (Interpolation and Correction) pipeline. Muscle forces are deduced from joint coordinates \mathbf{q} and joint torques $\mathbf{\Gamma}$. A first estimation is interpolated from the database for each joint. These solutions are mixed into a unique solution by a barycentric interpolation using the torque associated to each joint. The correction step finds a solution \mathbf{F} close to the first estimation that respects the dynamic equilibrium and the physiological properties.

The original paper did apply the method to a 2 dofs planar arm with 12 muscles (8 mono-articular and 3 bi-articular) performing simulated pointing tasks using a minimum jerk pointing model (a total of 18207 motions), and 3 cost functions were tested (two polynomial criteria and a min/max formulation). Results were particularly good, since the MusIC method found quasi optimal solutions in any case ten times faster than classical optimization. Results were particularly good with polynomial cost functions, whereas results of the min/max formulation was less well reproduced. Figure 2.5. show sample results of the method mimicking cost functions for a given set of motions. The interpolated forces were shown to be close to the optimized ones.

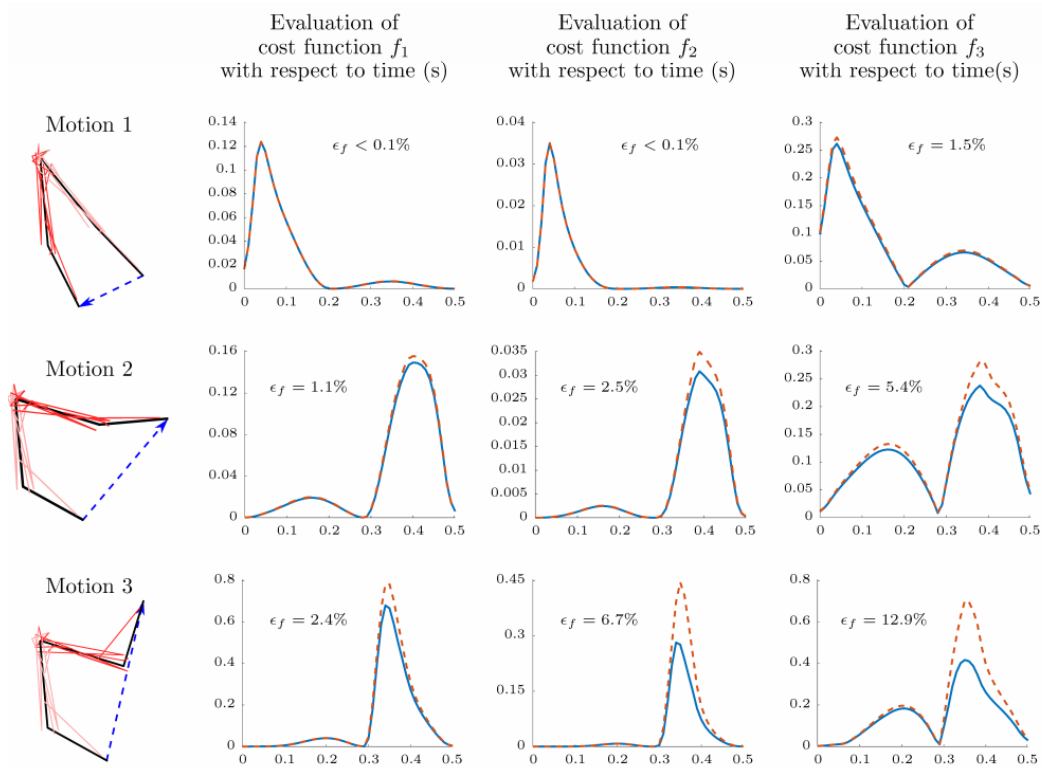


Figure 2.5. Sample results of the MusIC method mimicking various cost functions – 2nd order polynomial, 3rd order polynomial, min/max formulation respectively for 3 representative motions. Cost function values are less well reproduced for high level polynomials.

Globally, if this first validation was satisfying, several issues remained: first, if the method mimics satisfyingly classical cost functions, it does not guarantee that the results are valid regarding real activations or forces arising from a real motion. The MusIC method is just a shortcut to the classical force sharing problem encountered in any musculoskeletal simulation and asks for validation as any of those methods. Second, the model used here remained simple and asked for additional studies to be made on more complex – 3d – models. Third, the method was not tested with real data.

Last, the MusIC method required an additional computation time corresponding to the database generation time – about one hour. This time may seem important and widely increase the global computation time. Indeed, the database is subject-specific, and therefore it is necessary to compute one per subject in a given study with a given model. The database density was not handled in the original paper, and we arbitrary choose to make it “dense” enough without consideration to the performance of the method. This issue was the most important to deal with, and this is what we made in the adjunct paper that we shortly present here [57].

Considering the database generation computation time as a central problem, we decided to explore the accuracy of the method with respect to the density of the sub-databases. We assumed that i) the muscle forces interpolation error was directly correlated to the moment arm estimation error in the database and ii) the densities with highest trade-off between accuracy and off-line computation time for a scaled (to a subject) model were the same as whose defined on a generic model. We defined the term generic model as a non-scaled model.

Considering these two assumptions we developed a methodology assessing the accuracy of the method on real data and scaled models with respect to the accuracy of the moment arms deduced from the database discretization. Results of the study are summarized in the figure 2.6.

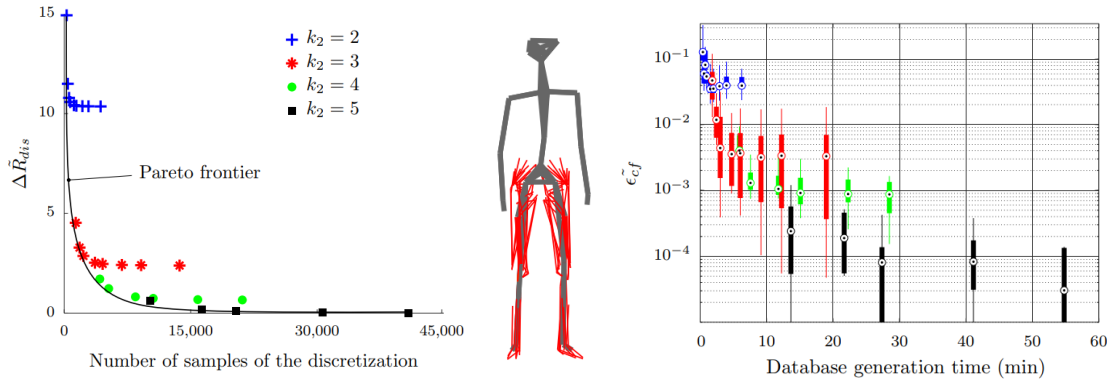


Figure 2.6. A summary of the results obtained in [57]. One can see the similarity of the results between the accuracy of the interpolated moment arms in the database (on the left) and the accuracy of the MusIC method (on the right). The model used in the middle was similar to the classical leg model of AnyBody. It is composed of 82 muscles and actuates 6 joints containing 12 dofs – 3 for the hip, 1 for the knee and 2 for the ankle. This model uses a majority of poly-articular muscles and allowed the method to be tested with a significant muscular coupling.

Considering the results on 10 subjects performing a standardized motion (activating all dofs successively), we found an interesting tradeoff between the database density and the MusIC method accuracy for a 82 muscles – 12 dofs lower limbs model. Indeed, a density of (4,4) (meaning 4 values to discretize the joint space of the main joint of a given sub-database and 4 values to discretize the joint space of the adjoining joints – joints influencing the muscle forces sharing solution for the main joint) led to a database generation time of less than 10 minutes.

The result was particularly interesting since the online forces estimation was more than 30 times faster than the optimization method (Sequential Quadratic Programming algorithm).

The second fundamental result hidden behind this is that the choice of the database density regarding the accuracy of the method can be made directly on a canonical model, without scaling it to any subject. This is a very interesting property of the method since when creating a new model, before applying it in a given study and a given subject (and therefore create the appropriate database), one can assess the moment arm discretization along the joint amplitude (left of figure 2.6.) in a very short time with a specific routine.

CONCLUSION

We made significant progress on the muscle forces estimation methods by defining a method able to mimic optimization results in a very short time, thanks to a database and an interpolation scheme. The method is fully implemented in our toolbox (CusToM, see Integrative Approach) and available to any user interested in it. The results of this work are very encouraging to enable live analysis sessions. Indeed, with this method, a final user or an expert can have a feedback about a motion that has just been captured in a very short time, at the kinematical, dynamical and muscle level. The method is still to be improved. One major limitation concerns the type of model that can be handled. The method cannot handle systems involving kinematical loops, since it asks for a precomputation of the torque at any joint to be applied. Extending it to closed loop systems would ask for strong adjustments in the method itself. A second flaw comes from the muscle model itself. In its current implementation, the MusIC method only consider the force-length relationship, that lead to only interpolate a solution from the joint angles. In the case that the method would be extended to force-velocity relationships, the interpolation should be made from angles and angular velocities, that complexify the search in the database. However, for a large set of applications, the method is usable as it is and may be enough to study the human at work for example. As future improvement, one can think about replacing the interpolation scheme by a learning method, even if it asks the questions of the independency of the results regarding the subject. In such cases, a specific learning scheme would have to take into account both motion and model parameters to be efficient.

RELATED PUBLICATIONS

- [Pontonnier et al. 2009]** Pontonnier, C., & Dumont, G. (2009). Inverse dynamics method using optimization techniques for the estimation of muscles forces involved in the elbow motion. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 3(4), 227.
- [Pontonnier et al. 2010]** Pontonnier, C., & Dumont, G. (2010). From motion capture to muscle forces in the human elbow aimed at improving the ergonomics of workstations. *Virtual and Physical prototyping*, 5(3), 113-122.
- [Muller et al. 2018a]** Muller, A., Pontonnier, C., & Dumont, G. (2018). The MusIC method: a fast and quasi-optimal solution to the muscle forces estimation problem. *Computer methods in biomechanics and biomedical engineering*, 21(2), 149-160.
- [Muller et al. 2018b]** Muller, A., Pontonnier, C., & Dumont, G. (2018). MusIC method enhancement by a sensitivity study of its performance: application to a lower limbs musculoskeletal model. *Computer Methods in Biomechanics and Biomedical Engineering*.

TOPIC 2: EFFICIENT SCALING

CONTEXT AND OBJECTIVE

As explained in the introduction of this section, the calibration of MSM to subjects (scaled to subject models) may benefit from motion based and external force-based methods. Even if some methods exist and may be used daily, as presented in introduction, they generally work as black boxes, meaning that they reduce a resulting error (kinematic error, dynamics residuals, torque production error) between experimental and model data, without checking if the parameter values they optimize make any sense.

The very first example of that comes at the geometrical level, when one tries to optimize the geometrical parameters of a model. As explained in the introduction, the most classical solution consists in adjusting both geometrical parameters and joint coordinates by minimizing the distance between model and experimental markers on a set of frames. This can be expressed as an optimization problem:

$$\left\{ \begin{array}{l} \text{At each frame :} \\ \min f(\mathbf{params}, \mathbf{q}_i) = \sum_{n_f} \sum_{n_p} \left\| \mathbf{X}_p(t_i) - \mathbf{X}_{p_m}(\mathbf{params}, \mathbf{q}_i) \right\|^2 \\ \text{Subject to:} \\ {}^j \mathbf{q}_i \in [{}^j q_{inf}, {}^j q_{sup}] \quad j = [1 \dots n_q] \end{array} \right. \quad (3)$$

With **params** a vector containing geometrical parameters (segment lengths, joint axes orientations, local marker coordinates) and **q_i** the vector of joint coordinates at frame *i*, **n_f** the number of frames selected for the optimization, and **n_p** the number of markers on the model.

This optimization can either be done by optimizing concomitantly [32,33] or successively [30,31] joint coordinates and geometrical parameters. Additional constraints (symmetry, distance to anthropometrics standards, proportional rules) can be added on geometrical parameters depending on their nature.

The problem with this scheme is that the unique validation criterion is generally the kinematic error, i.e. the distance between model and experimental markers...that is also the quantity to be minimized by the optimization. The method is likely subject to overfitting, since this error is due to the misestimation of the geometrical parameters, but also to the experimental measure errors and the kinematical model simplifications. In other words, the minimization can find a set of irrelevant geometrical parameters that lead to an optimal error.

This issue can be generalized to any layer of analysis, i.e. kinematical, dynamical and muscle. Moreover, scaling errors made at a given layer will also contaminate the other ones. Typically, inaccurate segment lengths will impact joint angles, that will impact joint torques and forces and therefore muscle forces estimation. At the same time, these segment lengths will also impact the musculotendon lengths and therefore change the intrinsic capacities of the muscle to generate forces in the model.

This issue led us to the two following contributions. First, understanding how errors propagate from one layer to another in a musculoskeletal model calibration. Second, how we can represent force generation capacities of subject that fits the data but still have a biomechanical/physical sense, at the muscle layer, for validation purposes. Such force generation model can therefore be used for muscle calibration in MSM.

The first study was performed within the thesis of Antoine Muller, whereas the second one was pursued during the post-doctoral fellowship of Diane Haering that was under my supervision with Georges Dumont, Nicolas Bideau and Guillaume Nicolas between 2015 and 2017.

KINEMATIC ERROR PROPAGATION IN DYNAMICS

Non-invasive Body Segment Inertial Parameters (BSIP) calibration consists in using motion capture and external force measurements to reproduce the motion dynamics and find the best BSIP that fit with these equations [58]. As said before, the idea may be to reduce the dynamics residuals, i.e. the remaining quantities in the dynamical equilibrium of the biomechanical model. In their work, [59] stated that “the magnitude of the vector of residuals gives an idea of the accuracy of the simulation, including the kinematic data, the mechanical model and the ground reaction forces’ measurements”. Thus, errors associated to kinematic data and force platform measurements directly influence optimization results. This may cause overfitting and distort the BSIP estimates. Indeed, [23] defined overfitting as “asking too much from the available data. Given a certain number of observations in a data set, there is an upper limit to the complexity of the model that can be derived with any acceptable degree of uncertainty”. Therefore, the idea of the study presented here [60] was to investigate the propagation of the uncertainty from kinematics results and force plates measurements to dynamics results in a whole-body biomechanical model inverse dynamics method. We captured the movements of 10 participants performing a standardized motion to evaluate the following hypotheses:

H1: regression methods compute acceptable body segment inertial parameters (BSIP) estimate for the inverse dynamics problem;

H2: dynamic residuals can be used to achieve a subject-specific BSIP calibration without overfitting.

The experimental data were used to drive a multibody human model scaled using a classical regression rule and dynamic residuals were computed and analyzed to investigate hypothesis **H1**. Then, a Monte Carlo-based method was applied to both kinematics and force plate measurements to determine the uncertainty due to these errors in the dynamic residuals. This approach allowed us to investigate hypothesis **H2**.

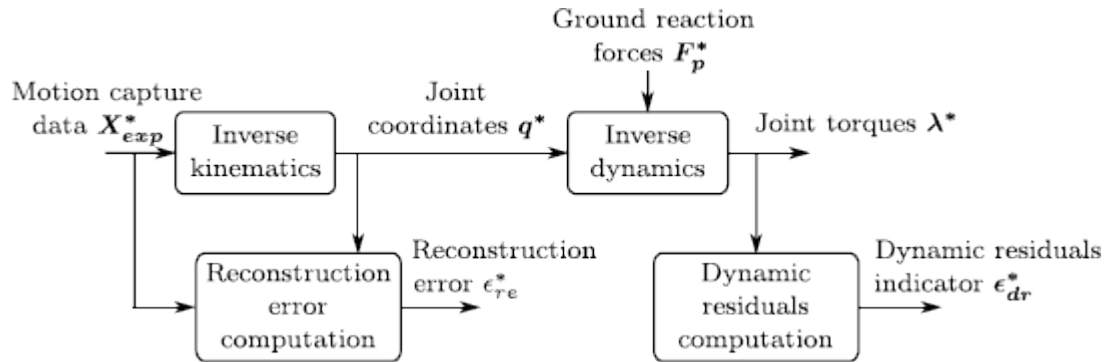


Figure 2.7. Inverse dynamics pipeline used with reference (non-disturbed) data. The accuracy of the results is quantified by assessing two indicators: ϵ_{re}^* (markers reconstruction error) and ϵ_{dr}^* (dynamics residuals indicator)

Following a classical inverse dynamics analysis pipeline as presented in figure 2.7., we used recorded data as a reference to compute two indicators of accuracy, that were the reconstruction error ϵ_{re}^* (distance between experimental and model markers averaged per frames and markers) and the dynamics residuals indicator ϵ_{dr}^* (root-mean-square of the dynamics residuals vector throughout the motion and normalized to the subject mass and size). The model used here was a whole-body model composed of 16 rigid segments linked by 15 joints and exhibits 35 degrees of freedom. Geometrical parameters were scaled thanks to the method described in introduction and BSIP were derived from [24].

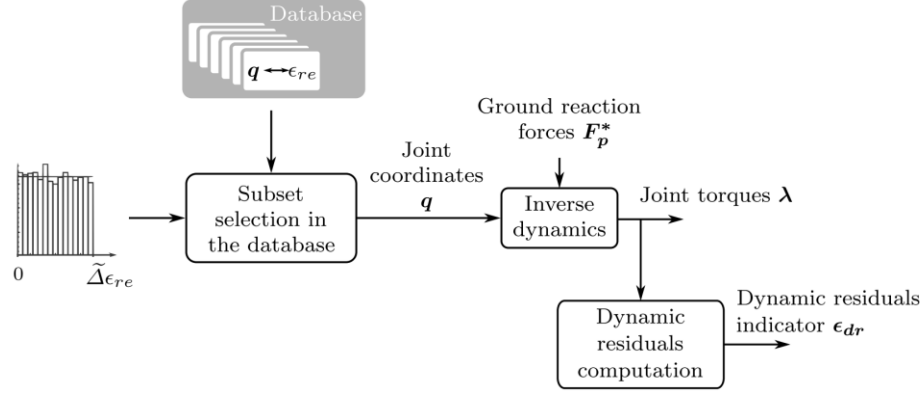


Figure 2.8. Inverse dynamics pipeline used with perturbed motion data. Dynamics residuals indicator is used to assess the amount of uncertainty on dynamics residuals brought by the motion uncertainty.

Thus, a database of perturbed motion data was computed from the reference one to feed the inverse dynamics pipeline (see figure 2.8). The dispersion of the dynamics residual indicators due to motion uncertainty $\Delta\epsilon_{dr}^{re}$ and the dispersion of the dynamics residual indicators due to ground reaction forces uncertainty $\Delta\epsilon_{dr}^{pe}$ were then assessed to understand how motion and forces uncertainties affected the dynamical quantities.

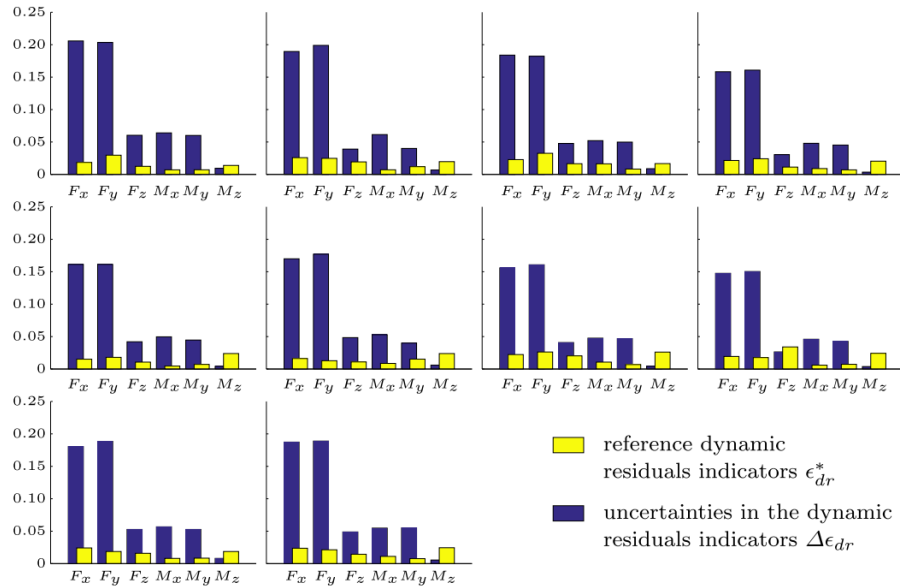


Figure 2.9. Reference dynamic residuals indicators and global uncertainties in the dynamic residuals indicators for each component. Each graph represents the results with one subject.

The analysis of the results led us to several conclusions that are of interest. First, we found that the geometrically scaled whole body model with BSIP obtained by regression led to force dynamics residuals of $2 \pm 0.6 \%$ and torque dynamics residuals of $1.3 \pm 0.7 \%$. These orders of magnitude were similar to [37] after a subject specific BSIP calibration. This result seemed to support H1, meaning that the regression-based BSIP evaluation was an acceptable estimate to calibrate the model. Since volunteers were regular people (healthy, no high-level athletes,

neither underweight nor obese: Body Mass Index within (18.5,30) range), the anthropometric data of [24] seemed close enough to subject-specific parameters.

Second, the dispersion due to motion uncertainty was proportional to the reconstruction error. This observation was fundamental since it allowed us to consider the uncertainty on dynamics residuals at an additional 100% of the reconstruction error to be equal to the one introduced by this error in the reference dynamics residuals. Considering this value, we also observed that the uncertainty due to the motion data was 5 orders of magnitude higher than the uncertainty due to ground reaction forces. Finally, comparing this uncertainty with the dynamics residuals of the reference data, as shown in figure 2.9., the uncertainties in the dynamic residuals are higher than the reference dynamic residuals, except for the vertical moment component (z-axis).

This final observation is fully rejecting **H2** as a valid assumption. Indeed, the residuals are here widely explained by the reconstruction error and minimizing them to achieve a BSIP calibration would lead to erroneous results – overfitting issues. Therefore, considering the experimental protocol and the multibody model used, hypothesis **H2** is refuted.

Even if motion uncertainty can be reduced in many ways (improving the kinematical model [61,62], taking into account STA reduction models [63,64], alternative inverse kinematics methods [17,59], using global inverse dynamics methods instead of iterative ones [65], better choosing data input [66]), this result is of importance since it illustrates one of the most fundamental issues asked by motion analysis and musculoskeletal simulation in general: calibration methods tend to overfit by adjusting parameters that are only partially responsible of the error to minimize. In this particular case, our final recommendation was i) to adjust BSIP only when it is really necessary (unconventional morphologies, amputees ...) ii) to add information to drive the BSIP adjustments – meaning that it is necessary to constrain the optimization problem with symmetries or proportional rules for example [67].

STRENGTH PROFILES: MODELING AND APPLIED ASPECTS

Joint strength models [68,69,70] are valuable representations of the torque generation capacities of a human, useful in direct assessment as well as in musculoskeletal modeling and analyses of human body, especially to characterize its strengths capacities with regard to a specified posture or task [71]. These models assume that muscles are viscoelastic actuators [72,73,74], resulting at the joint level in Joint Torque-Angle and Torque-Velocity Relationships (JTAR and JTVR respectively, and their coupling JTAVR). The interest of such models to scale the muscle layer of musculoskeletal models lies in the fact that from a limited set of experimental data, the muscle capacities can be extrapolated to the whole range of motion of a given joint and therefore scaled on this whole range [9]. A direct in-vivo estimation of the parameters of the muscle layer remains an issue, since it requires cadaveric, invasive or expensive measurements. Joint strength models are therefore useful to get these values indirectly.

Fitting such JTAVR envelopes to specific subject data while keeping their physiological meaning remains an issue. Basically, the data to fit consists in isometric and isokinetic measurements of joint torques in different angle and angular velocity conditions. No consensus exists on JTAR models: many models were proposed (cosine, quadratic, among others). Meanwhile, JTVR is mostly represented with hyperbolic functions [75,76], although it might not cover all the joint velocity range [77]. Logistic models also prove to be efficient in prediction of the torque values for extrapolated data [8]. However, such model loses most of its interest since it does not give any physiologically relevant information. For example, maximal strength and muscle compositions are useful in ergonomics [79,80]. We were therefore interested in finding relevant JTAVR models able to provide the torque generation capacities of a given joint on the whole range of motion for scaling purposes with physiologically relevant parameters. We ran an experimental protocol with 22 healthy subjects

(33 ± 6 years; 1.81 ± 0.07 m; 78 ± 9 kg). These subjects performed elbow isometric and isokinetic trials on a Con-Trex MJ® isokinetic dynamometer (CMV AG, Dübendorf, Switzerland, see figure 2.10.). Isometric trials consisted voluntary contractions hold for 5 seconds in flexion or extension at angles evenly spaced throughout the range of motion of the subjects. Isokinetic trials consisted in concentric-passive cycles at $60^\circ \cdot s^{-1}$, $120^\circ \cdot s^{-1}$ and $180^\circ \cdot s^{-1}$ in flexion and extension.



Figure 2.10 Experimental set up. The participant is seated and attached to the ConTrex dynamometer in upright position with the arm along his side. The axis of the dynamometer is aligned with the epicondylitis axis with the elbow flexed at 90° .

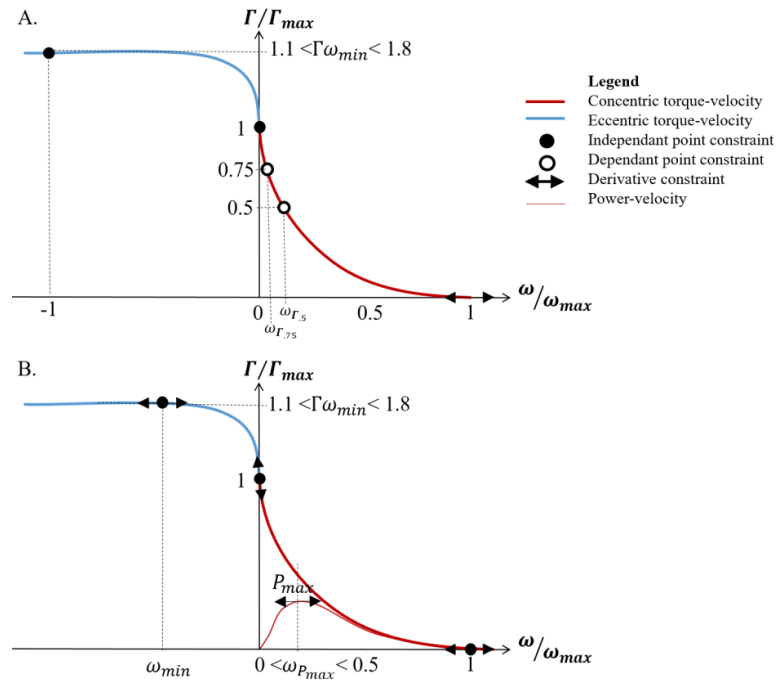


Figure 2.11. Anderson-based (A) and power-based JTVR models. Both models induce continuity and derivative constraints preserving the shape of the curve along the velocity range.

We fitted 5 JTAR and 2 JTVR to this data. The JTAR were issued from the literature (Normal [74,81], Quadratic [82,70], Cosinus [83], Cubic [84] and Sinus-exponential [75] model). The JTVR were the one based on the work of Anderson (a cosinus based model with an additional parameter [70]) and a new one, supposed to be more physiologically relevant, based on the maximal power velocity definition. We wanted to test the capacity of such a model to correctly fit the data and provide meaningful physiological information. Without considering specifically the equations behind these models, the parameters they introduced were the following:

Parameters		Limits	
Γ_{max}	Max. isometric torque	$0.75 \Gamma_{meas}$	$1.25 \Gamma_{meas}$
RoM	Max. isometric range of motion	0	π
α_0	Isometric optimal angle	$\pi/6$	$5\pi/6$

Table 1 JTAR physiological parameters

Model	Parameters			Limits	
Anderson-based torque-velocity model	P_1	$\omega_{\Gamma_{.75}}$	Velocity at 75% of maximal isometric torque	0	π
	P_2	$\omega_{\Gamma_{.5}}/\omega_{\Gamma_{.75}}$	Ratio between velocities at 50% and 75% of maximal isometric torque	1.9	2.1
	P_3	E	Eccentric to concentric torque index	.1	.8
Power-based torque-velocity model	P_1	ω_{max}	Max. concentric velocity	$\pi/3$	5π
	P_2	$\omega_{P_{max}}$	Velocity at maximal power	0.25	0.4
	P_3	$\omega_{min}/\omega_{max}$	Max. eccentric to concentric velocity ratio	-1	-0.1
	P_4	$\Gamma_{ECC}/\Gamma_{CON}$	Max. eccentric to concentric torque ratio	1.1	1.8

Table 2 JTVR physiological parameters.

Results of the study had to be considered from data fitting and interpretation points of views. Concerning data fitting, the most relevant JTAR model for the elbow strength representation seemed to be the quadratic one. This result is logical since the maximal strength of the elbow is approximately obtained at half of the flexion range. Therefore, a symmetrical model such as the quadratic one has more chances to be efficient in this case. Associated to this JTAR model, both JTVR models fit the data with a similar level of performance.

In terms of physiological relevance of the parameters, JTAR parameters obtained with the quadratic model were all in range that the literature confirms. For example, the Γ_{max} value remained in a range of 63 N.m to 69 N.m and the flexion/extension ratio from 0.95 to 0.97, that is consistent with the literature [73,85,86]. The resulting ranges of motion RoM were larger than the anatomical reference [87], however it was the case for all the JTAR models, since the strength model goes beyond the real elbow range of motion, limited by the osteo-articular structure. Finally, the isometric optimal angle α_0 of 77° in flexion and 72° in extension for the quadratic model were close to observed average angles [88,89]. Therefore, all these parameters were correctly predicted by the model from the data and are meaningful for analysis.

Regarding JTVR models, we first focused on the concentric velocity at maximal power, $\omega_{P_{max}}$. Due to its relationship with muscle composition [87], linking mechanical and physiological muscle functions, the implementation of this parameter in the power-based model seemed relevant for sports, rehabilitation or ergonomics applications [90]. Optimized $\omega_{P_{max}}$ values, between $404^\circ.s^{-1}$, and $561^\circ.s^{-1}$, were about two times larger than $\omega_{P_{max}}$ values measured on isokinetic dynamometer for thigh muscles [91]. For further work, a combination of $\omega_{P_{max}}$ measurements with Hill-model correction and electromyography should be investigated.

As a conclusion, the power-based JTVR model seemed relevant to fit the data and propose physiologically relevant parameters to associated to a given subject. These results can be really interesting for ergonomics, since it can give an overview of the force capacities of a subject, in a similar manner as the Force Feasible Set for example [71].

CONCLUSION

The scaling of the musculoskeletal models is a major concern for musculoskeletal simulation, and we see a large turn of the research community to the imagery methods. However, such methods may be relevant for clinical applications, not for industrial/ergonomics ones, due to the availability of the equipment and data processing steps. Therefore, there are still a lot of room to propose alternative (motion or force based) calibration or scaling methods, offering a satisfying tradeoff between accuracy and usability. We exposed in this section several works about scaling of musculoskeletal models, from motion and external forces measurements. Obviously, this work is far from being exhaustive, dependent from the body parts to be studied, the data to be collected and many other issues. Multiple enhancements and research questions are still to be solved. Particularly, overfitting issues are still prevalent in minimization-based methods and most of these developments must be challenged with reference data. For example, geometrical parameters of a musculoskeletal model must be compared to image-based measures to be validated, additionally to any validation of the kinematics. This is some of the issues currently pursued within the thesis of Pierre Puchaud that I currently supervise as a director with Nicolas Bideau and Georges Dumont.

Considering joint torques envelopes, a few considerations may offer relevant research perspectives. First, how we can use them efficiently in musculoskeletal modeling? Even if envelopes are valuable representations of muscle capacities at a given time, the link to the muscle force generation capacities is leading to an indeterminate problem (one torque for multiple muscles forces relationships composed of multiple parameters). Second, we know that these envelopes evolve with internal (e.g. fatigue [91]) and external (e.g. cold [92]) factors. Therefore, assessing these envelopes evolution with regard to these factors may be relevant to take into account work conditions more accurately.

RELATED PUBLICATIONS

- [Muller et al. 2016]** Muller, A., Germain, C., Pontonnier, C., & Dumont, G. (2016). A simple method to calibrate kinematical invariants: application to overhead throwing. In ISBS-Conference Proceedings Archive (Vol. 33, No. 1).
- [Muller et al. 2017]** Muller, A., Pontonnier, C., & Dumont, G. (2017). Uncertainty propagation in multibody human model dynamics. *Multibody System Dynamics*, 40(2), 177-192.
- [Haering et al. 2019]** Haering, D., Pontonnier, C., Bideau, N., Nicolas, G., Dumont, G. (2019). Using torque-angle and torque-velocity models to characterize elbow mechanical function: Modelling and applied aspects. *Journal of Biomechanical Engineering*
- [Puchaud et al. 2019]** Puchaud, P., Dumont, G., Bideau, N., Pontonnier, C. (2019). Knee Torque Generation Capacities Modelled with Physiological Torque-Angle-Velocity Relationships, *Computer Methods in Biomechanics and Biomedical Engineering*, Proceedings of Congrès de la Société de Biomécanique 2019

TOPIC 3: MUSCULOSKELETAL SIMULATION IN INDUSTRIAL CONDITIONS

CONTEXT AND OBJECTIVE

Motion analysis, even more musculoskeletal simulation, is often limited to lab conditions, since it asks for accurate and exhaustive data to be efficient. Indeed, as explained in introduction of this section, most of the works dealing with musculoskeletal analyses rely on optoelectronic motion capture data completed with ground reaction forces measurements through force platforms. These conditions are clearly restrictive and hamper the democratization of such methods for day-by-day analyses in “natural” or occluded environments. Moreover, the use of force platforms limits the area of investigation to the area of contact and prevent the use of inverse dynamics methods when other segments are in contact (hands for example).

Following the goal to democratize the use of musculoskeletal analysis tools for ergonomics, we explored methods to be used in occluded environments with a very limited setup, corresponding to the first study presented in this section. We also proposed methods enabling an estimation of external forces applied to a subject without any direct measure of these forces, enabling motion analysis in large fields without any force platform or sensor. It corresponds to the second study developed in this section.

The first study was performed as a collaboration between two PhD students during their thesis, Pierre Plantard, supervised by Franck Multon, and Antoine Muller that has already been presented. It consisted in proposing an inverse dynamics pipeline based on Kinect data for occluded environment. The second study was a post-doctoral work of Antoine Muller under my supervision and the one from Georges Dumont. It consisted in a motion-based external force prediction method for hands and feet validated on lifting tasks.

USING KINECT DATA IN INVERSE DYNAMICS FOR ERGONOMICS

In this work, our purpose was to assess the feasibility of an inverse dynamics analysis based on Kinect data in an occluded -close to ecological conditions – environment. For this purpose, we applied some of the developments on inverse dynamics realized by Antoine Muller with data collected and processed thanks to the

method developed by Pierre Plantard during his PhD thesis. Indeed, Pierre developed a Kinect real-time processing method able to increase the reliability of the postural data classically obtained by a Kinect. Such a depth camera is known to encounter severe issues in occluded environments, when the body is partially seen by the camera. In such a case, the occluded members positions tend to be badly estimated. Thanks to the use of a filtered pose graph and a postural database, the method assesses the reliability of each segment of the postural position evaluated by the Kinect and use the most reliable ones to reconstruct from previous events and the database a better postural candidate. The method has shown its efficiency with several publications [93,94].

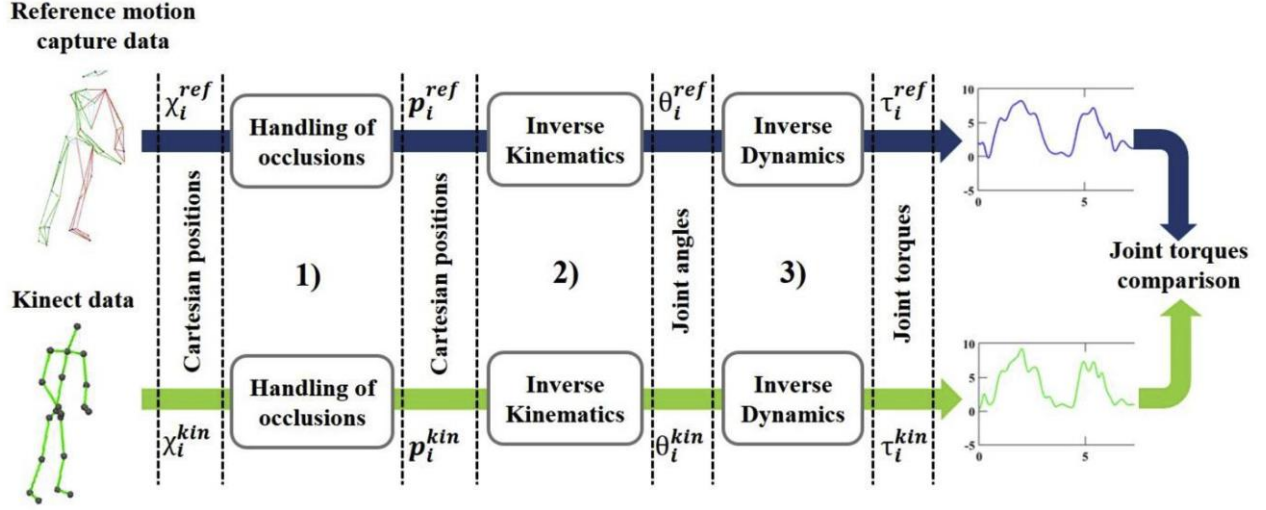


Figure 2.12. Overview of the two pipelines allowing the joint torque comparisons, using both Kinect data (in green) and reference Vicon data (in blue). Joint torque estimation was divided in three steps: 1) Handling of occlusions; 2) inverse kinematic computation and 3) inverse dynamics computation.

To evaluate dynamics quantities computed from Kinect data we developed a framework providing joint torques for a whole-body model with classical optoelectronic data, and for an upper limb model with Kinect data, as shown in figure 2.12.

The difference between the input data provided by each motion capture system required to process dynamic estimation separately. Classical motion capture was processed by reconstructing occluded trajectories and low-pass filtering (5Hz). A classical inverse kinematics method [16] was applied on a whole-body model with 35 degrees of freedom, as shown in figure 2.13. (left). Kinect data was corrected with the method proposed by [93] as explained above. Thus, using the model presented on the right of the figure 2.13., the different segment frames were computed thanks to the experimental positions of joint provided by the correction method. From kinematics of the biomechanical model, the joint coordinates were identified in agreement with the ISB recommendations [95]. Since the hand position obtained with the Kinect was uncertain, the wrist was considered as fixed. The pronation and supination of the forearm were not considered by the arm joint position, so the elbow joint was modeled as a revolute joint. The limb lengths were identified from the raw data processing method. BSIP were estimated with the regression method proposed by [24].

For both methods, the joint torques were obtained from joint positions, velocities and accelerations using a recursive Newton-Euler algorithm [18].

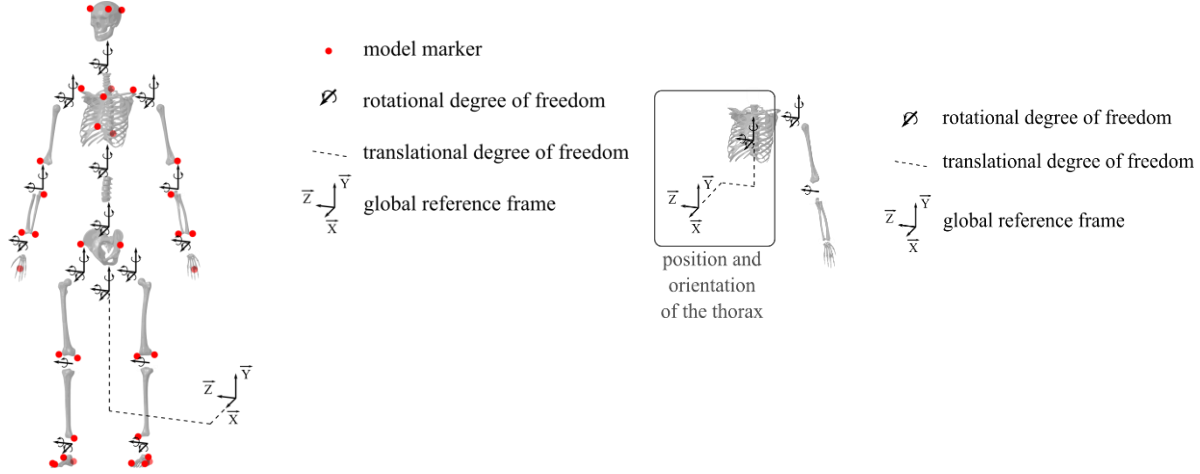


Figure 2.13. (Left) Kinematics of biomechanical model and model markers position for the reference inverse dynamic pipeline. A virtual 6 degrees of freedom (DoF) joint connects the pelvis to the global reference frame to convert a floating-base system into an equivalent fixed based system. (Right) Kinematics of biomechanical model for the Kinect inverse dynamic pipeline.

To generate comparison data between both methods, we simulated a handling task with severe occlusion conditions. 12 male participants (age: 30.1 ± 7.0 years, height: 1.75 ± 0.046 m, mass: 62 ± 2.7 kg) were volunteers to participate in this study.

The subjects had to perform Getting and Putting tasks, with an empty cardboard box, as depicted in the right part of figure 2.14. In this protocol, we have chosen an empty cardboard box to have a minimum weight manipulated by the subject (200 g), leading to negligible external forces but introducing occlusions. The Getting task consisted of a carrying box motion from initial position to the front of the hips. The Putting task involved replacing the box to the starting position. The initial position of the box was set at two possible locations to generate motion variability, represented by P1 and P2 on the figure 2.14. (right).

The manipulated box was supposed to generate occlusions according to its placement in relation to the position of the Kinect. We tested different scenarios with and without the box, and various positions of the Kinect to analyze the impact of different types of occlusions:

- NB: without box condition. The subject had to mimic the manipulating motion without using a box, leading to a situation without occlusion. Under this condition, subjects were simply asked to reach the position with their hands where the box would normally be. The Kinect was placed in front of the subjects, as recommended by Microsoft. This scenario allowed us to test the robustness of the Kinect in optimal conditions.
- B: with box. The manipulation was realized with the box, leading to occlusions of body parts, as in real work conditions. The Kinect camera was again placed in front of the subject, as recommended by Microsoft.
- B45: with box and camera placement 45° to the right. The only difference with condition B was that the Kinect was placed 45° on the right of the subject. This type of non-recommended Kinect placement generally occurs in cluttered environments. Under this condition, the risk of occlusions was greater than in all previous conditions.

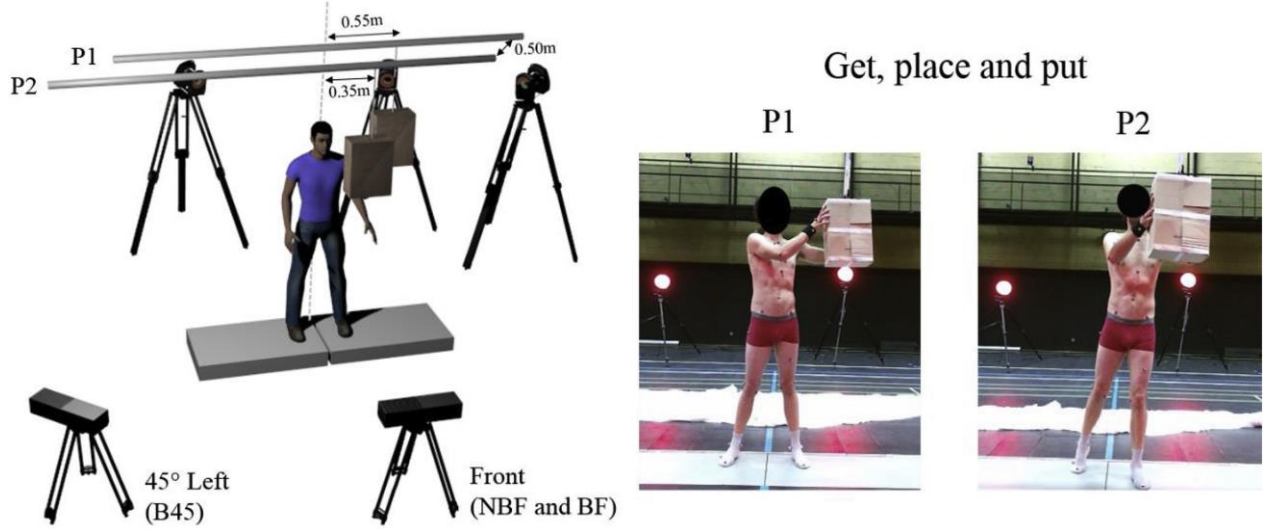


Figure 2.14. Experimental set-up with two placements (P1: object on the left or P2: front-left), with two Kinect positions (NBF and BF: in front or B45: 45° left).

Joint angles θ^{ref} and θ^{kin} and torques τ^{ref} and τ^{kin} were computed from both data sources following the method described above. After a validation of what was considered as the reference data (θ^{ref} , τ^{ref}) by analyzing the dynamics residuals during the task (see previous focus about uncertainty propagation), joint angle trajectories and joint torques trajectories among YXY shoulder axis and the Z elbow axis were compared by computing the cross-correlation between signals. Additionally, an intra-class correlation (ICC) was computed between maximal torques obtained by each method for each task to assess the consistency of this value. Finally, RMSE and nRMSE during dynamic phases of the task were computed to complete the quantitative comparison of both methods.

Results can be summarized as follows. First, joint angles were highly correlated, the lowest correlation result being about 0.65 in the most occluded condition (Box in front position P2 and Kinect in front position B) for the Y_2 axis. Second, joint torques were also highly correlated (mean $r = 0.77$ for all conditions and all joints), excepted for the Y_1 (orientation of the left shoulder elevation plane) shoulder axis (0.26 to 0.5 depending on the conditions). Maximal joint torques per task were highly correlated between both methods (0.98, 0.98, 0.99, 0.99 along the Y_1 , X and Y_2 shoulder axis, and along the Z elbow axis respectively). RMSE and nRMSE results showed significant differences between both methods for all the joints, with an error of approx. 29.5% in mean for all the axes.

From these results, several observations can be made: first, cross-correlation and intra-class correlation (ICC) showed that torques estimated with the Kinect on the considered joints were consistent with the reference. ICC results were particularly high, leading to the conclusion that the method using Kinect data was able to discriminate properly two different work situations in terms of torque level. nRMSE may show that the system estimated quite poorly the absolute values of the joint torques. However, ICC proved that such a method may be used to assess the torque of a given task and compare it to another task. This result is really encouraging since it indicates that a Kinect placed in an industrial environment may be usable to assess internal forces arising from a given task.

Obviously, these results are still to be confirmed on a larger cohort and with more discriminative work situations. Several other limitations must be mentioned: first, the kinematic model used with the Kinect data is still quite poor, being unable to capture small details such as hand motions that can be of high interest in WMSD prevention. Second, the 30 Hz acquisition frequency of the Kinect is limiting the estimation of dynamic quantities to relatively slow motions. Last, the current study did not consider any external forces measurement since the box was supposed to apply a negligible load on the subject.

This last issue is fundamental for more strenuous tasks that are generally encountered in the industry, such as handling tasks. Therefore, we developed the method proposed in the following contribution, dealing with external forces prediction from motion data only.

PREDICTING EXTERNAL FORCES FROM MOTION DATA

Following the idea to enable an easier and more applicative use of motion analysis, especially musculoskeletal analysis, one of the fundamental issues is the restriction of the field of analysis to the force measurement surfaces being in contact with the subject. Therefore, there is a need of methods able to estimate dynamical quantities (joint torques, muscle forces) without this restriction. This is particularly true for onsite ergonomics studies, in which no instrumentation of contacts can be realized, but also in sports sciences for ecological situations to be studied.

Several methods proved their efficiency to predict from motion only the external forces equilibrating the body in dynamics terms (machine learning methods [96], analytical methods [97,98], and optimization methods based on contact points [99,100]). However, none of these methods was applied to other contact surfaces than feet. Therefore, there was a need of a method able to predict both contact forces and moments at the feet and the hands. This is obviously useful for ergonomics, especially for handling and carrying tasks that are very common in the industrial context. The study presented here deals with this issue, proposing a methodology able to predict contact forces and moments at hands and feet for asymmetric lifting tasks [101].

To this end, we developed an experimental protocol consisting in the lifting and carrying of an instrumented box, enabling the record of 13 subjects (age: 27 ± 7 years old, height: 177 ± 4 cm, mass: 73 ± 15 kg) that participated in this study. We considered a cycle as a set of three elementary movements from one location to one other as depicted in figure 2.15. The load to carry was a custom load box of 6.9 kg with two handles. One of the handles was equipped with a 6-dof force sensor (AMTI MC3A). Motion of subjects was captured thanks to a VICON system sampled at 200 Hz. The marker set was a whole-body marker set inspired from the ISB recommendations. Two force platforms (AMTI, sampled at 1000 Hz) were used to measure the feet contact forces separately. Motion of the load box was also captured for evaluation purposes with 9 markers.

The prediction method consisted in the application of 3 successive steps to the data.

First, a grip/deposit event detection was applied to the data. This step was mandatory to know when the box was carried or not by the subject. It consisted of a neural network trained to detect the most probable instants for grip deposit events. The neural network was trained with 5 descriptors based on the markers placed on both hands (distance between the markers, velocity and acceleration magnitudes of each marker). During the learning phase, a video recording was used to manually detect the grip and deposit events. A normal distribution centered on the identified grip and deposit events was applied as the probability to have such an event during this time window. Using this trained neural network, the probability to detect a grip or deposit event was evaluated for every subject and every trial at any instant. The method was validated thanks to a leave-one-out validation method.

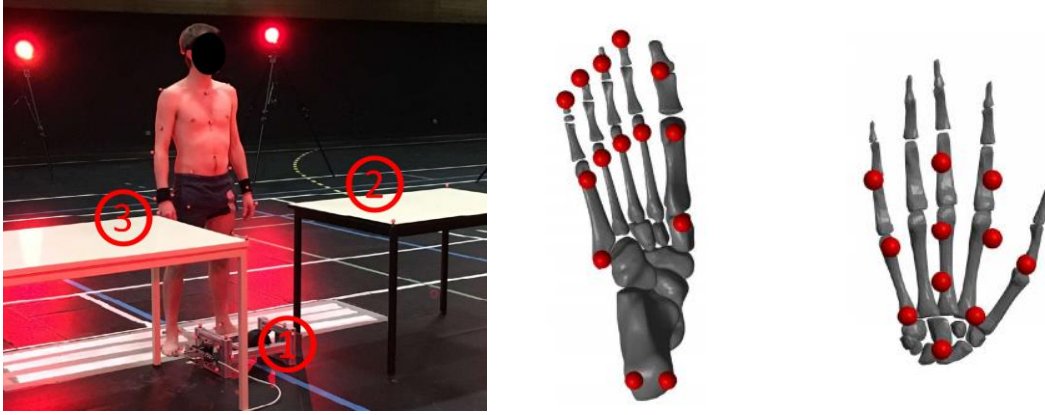


Figure 2.15. (Left) Experimental setup. The numbers represent the zones where the subject must deposit the box. (Right) Hand and Foot contact points definition for the prediction method.

Second, a reconstruction of the load motion was computed to apply rigid bodies dynamics laws on it. To be close from ecological conditions, it was necessary to be able to reconstruct the load motion without any marker placed on it. Markers placed on the load were used to validate this method. The load motion was approximated from the motion of the markers placed on both right and left hands. It was assumed that the load did not rotate around the axis defined by both grasping points (handles).

Last, using the two first steps result and the subject motion capture data, the prediction method was applied to a whole-body biomechanical model composed of 18 rigid segments linked by 17 joints corresponding to 41 degrees of freedom, to compute the external efforts applied on the feet (GRF&M) and external efforts applied on the hands (LCF&M). The geometrical parameters were calibrated to the subject, and body segment inertial parameters (BSIP) were computed from [24]. A set of contact points was defined to map the contact areas [99,100] as shown in figure 2.15.

The prediction problem formulation depended on the considered phases of the cycle: we distinguished phases without load carriage from those with load carriage.

The prediction problem without load carriage can be summarized as follows:

$$\begin{aligned}
 & \min_F \sum_{i=1}^{2N_f} \|F_i\|^2 \\
 \text{s. t.} \quad & \mathbf{M}_s(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}_s(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}_s(\mathbf{q}) + \boldsymbol{\lambda}_s + \mathbf{E}_s = \mathbf{0} \\
 & \forall i \in \llbracket 1, 2N_f \rrbracket, F_i < F_i^{\max}
 \end{aligned} \tag{4}$$

Where, by isolating the biomechanical model, $\mathbf{M}_s(\mathbf{q})$ is the inertia matrix, $\mathbf{C}_s(\mathbf{q}, \dot{\mathbf{q}})$ is the centrifugal and Coriolis force vector, $\mathbf{G}_s(\mathbf{q})$ is the gravity force vector, $\boldsymbol{\lambda}_s$ is the generalized internal force vector, \mathbf{E}_s is the generalized external force vector and F_i^{\max} is the vector containing the maximal forces available for the contact point i . This problem was solved at each frame using an SQP algorithm.

When the load was carried, the equations of motion of the load were added to the constraint of the minimization problem:

$$\begin{aligned}
& \min_F \sum_{i=1}^{2N_f} \|F_i\|^2 \\
s. t. \quad & \mathbf{M}_s(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}_s(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}_s(\mathbf{q}) + \boldsymbol{\lambda}_s + \mathbf{E}_s = \mathbf{0} \\
& \mathbf{M}_l(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}_l(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{G}_l(\mathbf{q}) + \mathbf{E}_l = \mathbf{0} \\
& \forall i \in \llbracket 1, 2N_f \rrbracket, F_i < F_i^{max}
\end{aligned} \tag{5}$$

Where, by isolating the load, $\mathbf{M}_l(\mathbf{q})$ is the inertia matrix, $\mathbf{C}_l(\mathbf{q}, \dot{\mathbf{q}})$ is the centrifugal and Coriolis force vector, $\mathbf{G}_l(\mathbf{q})$ is the gravity force vector and \mathbf{E}_l is the generalized external force vector. The external efforts vector \mathbf{E}_s contained the external forces applied on the feet and the external efforts vector \mathbf{E}_l contained the external forces applied on the hands.

For both methods, at each frame, we ensured that each active contact point was sufficiently close to the floor and almost without motion [99,100]. The distance and velocity thresholds were respectively 0.02m and 0.8m/s. When a contact point was respecting the thresholds, the associated force was limited to 0.4BW (Body Weight) and had to respect the Coulomb's law of friction. A friction coefficient of 0.5 was used here [99,102]. The results of the method were evaluated at 3 different levels: first, the grip/deposit event prediction was validated with a leave-one-out cross validation. Second, the predicted GRF&M were compared to those measured by the force platforms, and the LCF on the right hand were compared to those measured by the force sensor mounted in the handle (RMSE and relative RMSE were computed for all of these forces). Last, the L5/S1 joint moments were computed with predicted and measured data and compared. This last validation seemed relevant since L5/S1 joint moments are a consistent measure of back loading for handling tasks [103].

The grip/deposit event prediction gave satisfactory results since on the whole number of events to predict (312), 8 only were found to be outside the uncertainty areas, with a very low error on these "badly" predicted events. The chosen descriptors of the grip and deposit moments were then satisfactory and the method seemed relevant and robust to get the current state of the task (carrying the load or not).

Figure 2.16. depicts a classical contact and ground reaction forces prediction on a sample trial. These representative results show that the relative error was the lowest on the vertical GRF which corresponds to the weight component. The results in the carrying phase (between the two orange areas) seemed not to be affected by the contact efforts on the hands. The most important errors were observed on the medio-lateral forces. Indeed, the subject probably generated some forces in this direction to improve his stability. Since the method is based on a minimization, it cannot predict forces that are not directly responsible of the motion. This trend is also visible on hands where the subject applied traction or compression forces to better grip the load. In the same manner, these forces were impossible to predict without additional sensors. Moreover, during uncertainty phases, the subject had indirectly a contact with the ground or the table where the load was placed. This contact was not considered in the proposed method, generating prediction errors.

The global RMSE for the vertical forces was 17.9N and 20.3N for each foot, corresponding to 0.24N/kg and 0.28N/kg. These errors were lower than those presented in the literature for walking motions, whatever the prediction method: empirical functions [98] (0.90N/kg), machine learning [96] (0.73N/kg) or a contact model [100] (between 0.52N/kg and 0.91N/kg).

The RMSE for the antero-posterior axis was below 0.10N/kg since the efforts values were very low due to the performed tasks. The medio-lateral forces component obtained the most important errors (0.37N/kg and 0.45N/kg for each foot corresponding to 34.8% and 40.7%) which confirms the observations previously made on figure 2.16. Also, the GRM were in the same order of magnitude as those reported previously [100]. Considering all these results for the phases with no load, one can conclude that the method presented here reproduced similar results as in the literature in similar cases.

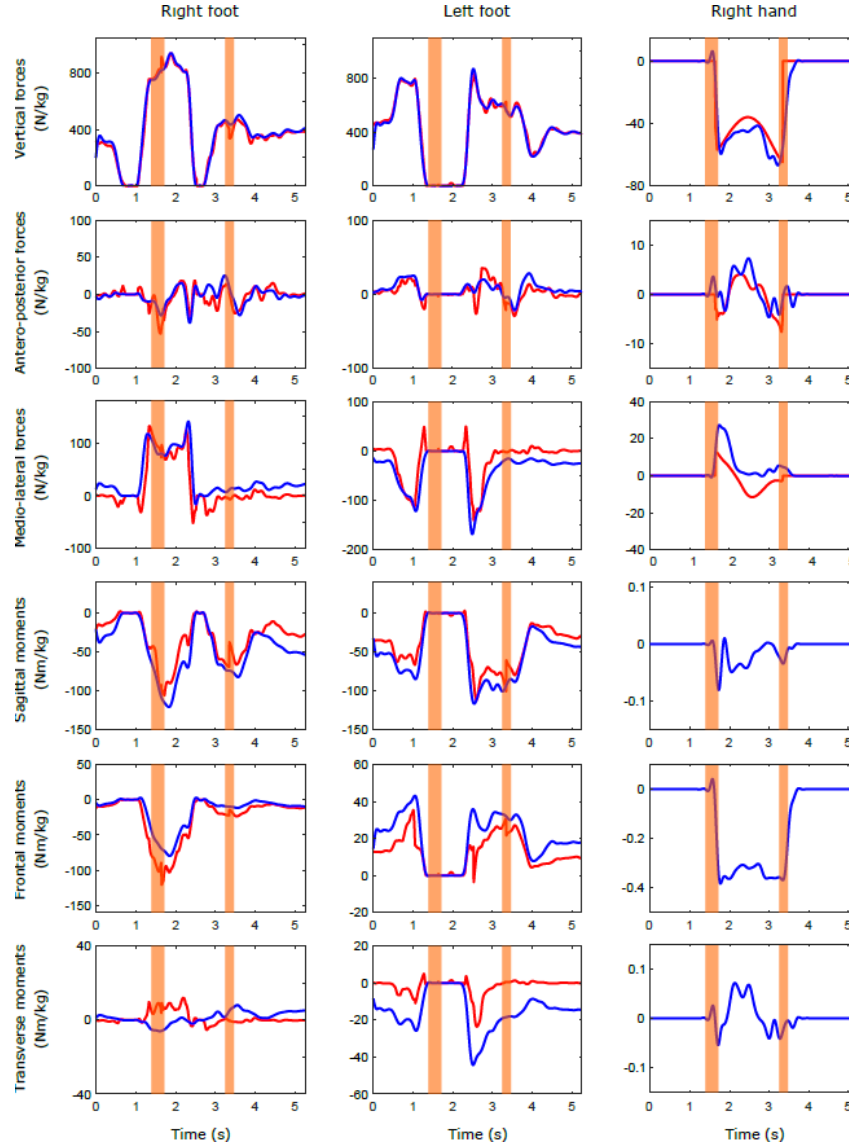


Figure 2.16. - Representative example of predicted and measured GRF&M and LCF for a grip/deposit cycle. The blue curve corresponds to the measured data, the red one corresponds to the predicted data. The orange areas represent the uncertainty phases (identified with the video). Inside these areas, the subject was in contact with the load but without completely carrying it.

The RMSE error on the L5/S1 joint moments estimation were $18.7 \pm 11 \text{ Nm}$, $10.6 \pm 7.8 \text{ Nm}$ and $12.6 \pm 9.6 \text{ Nm}$ on sagittal, frontal and transverse axis, respectively. The associated rRMSE are $9.9 \pm 5.8\%$, $8.9 \pm 6.5\%$ and $37 \pm 36\%$. Compared to uncertainties reported in the literature studying handling tasks by inverse dynamics approaches [99,100,101]. These values are of the same order of magnitude. Moreover, for the sagittal axis, the relative error was lower than 10%. This axis contains the most important moment values and is the most studied in handling tasks assessment in the literature.

Therefore, even if several limits can be reported on the design of the method (arbitrary parameters/thresholds in the method, anthropometrics-based BSIP, contact points design), it estimated the GRF&M and the LCF

during asymmetric handling tasks with a small margin of error, and with the subject motion as a unique source of experimental data. This estimation could be used to compute kinetics variables as back loading with an acceptable error. Next improvements should first be to use out-of-the-lab motion capture devices (Depth cameras, IMUs...) to unleash the restriction on the optoelectronic data, and the development of a more robust grip/deposit event detection. Indeed, this last limitation is of importance since in the current study, the handling of the load was particularly constrained by the handles. In classical handling/carrying tasks, subjects exhibit much more variability in their grip/deposit strategies, that is a challenging issue to automatically detect these events. In conclusion, thanks to this method, inverse dynamics studies are not limited anymore to motions where the body is in contact with force sensors to estimate the external forces. It may be extremely useful in work tasks assessment or sport gesture analyses, opening a wide range of applications. It indicates that we can develop and analyze more complex experimental protocols with a higher level of generalizability to real tasks in a motion analysis lab.

This work has recently been extended successfully to a large cohort of subject handling boxes on a large force platform [107], and we also applied it to an experimental dataset of fencing lunges, showing its limits for static/quasi-static tasks and its strength for dynamic ones [108]. Results showed that there was some unexpected solutions that are loading inefficiently the joints of the model. It militates to an extension of the method to minimize at the same time the internal forces, to enforce a more physiologically plausible solution.

CONCLUSION

These two contributions showed enthusiastic results for the development of onsite, real time analyses of motion as a decision support for ergonomists. Obviously, these are parts of a more complex puzzle, since one may think that coupling both studies may lead to an optimal setup for onsite analysis. However, coupling a Kinect with a force prediction method raises additional challenges to be solved. For example, the Kinect data exhibit large position jumps from one frame to one other, leading to inaccurate distal segment positions that are totally incompatible with a force prediction method that needs contact information to be efficient. A solution could be to couple such a system with a pressure map on the ground, giving contact information at any time to the method.

RELATED PUBLICATIONS

- [Plantard et al. 2017]** Plantard, P., Muller, A., Pontonnier, C., Dumont, G., Shum, H. P., & Multon, F. (2017). Inverse dynamics based on occlusion-resistant Kinect data: Is it usable for ergonomics? *International Journal of Industrial Ergonomics*, 61, 71-80.
- [Muller et al. 2019a]** Muller, A., Pontonnier, C., & Dumont, G. (2019). Motion-based prediction of hands and feet contact efforts during asymmetric handling tasks. *IEEE Transactions on Biomedical Engineering*.
- [Muller et al. 2019b]** Muller, A., Pontonnier, C., Robert-Lachaine, X., Dumont, G. & Plamondon, A. (2019). Motion-based prediction of external forces and moments and back loading during manual material handling tasks. *Applied Ergonomics*.
- [Pontonnier et al. 2019]** Pontonnier, C., Livet, C., Muller, A., Sorel, A., Dumont, G., Bideau, N. (2019). Ground Reaction Forces and Moments Prediction of Challenging Motions: Fencing Lunges. *Computer Methods in Biomechanics and Biomedical Engineering, Proceedings of Congrès de la Société de Biomécanique 2019*.

TOPIC 4: INTEGRATIVE APPROACH

CONTEXT AND OBJECTIVE

All the works presented in the previous focuses of this section are militating for an easier use of musculoskeletal analysis in ergonomics. Therefore, it was necessary to integrate all this work in a unique framework, easy to handle for any user, and easy to develop with for researchers. This necessity was even more obvious that at a stage, most of the research projects in which I am involved are more less related to a part of the scheme presented figure 1.2. Therefore, we decided to integrate all our work in a unique framework, called CusToM for “Customizable Toolbox for Musculoskeletal Simulation”. As it is extensively presented in the following section, the toolbox was also an opportunity to tackle several usability issues that we already mentioned. First, we made it customizable enough to mix between body part models, between muscle sets and between marker sets. We also made it usable for many different inputs (motion capture, IMUs). Finally, we developed user interfaces making it usable by any on-coder people interested in musculoskeletal analysis in a very short time.

CUSTOM

Customizable Toolbox for Musculoskeletal simulation (CusToM) is a MATLAB toolbox aimed at performing inverse dynamics based musculoskeletal analyzes [109]. CusToM exhibits several features. It can generate a personalized musculoskeletal model, and can solve from motion capture data inverse kinematics, external forces estimation, inverse dynamics and muscle forces estimation problems.

According to user choices, the musculoskeletal model generation is achieved by assembling automatically pre-registered osteoarticular models or sub-models (body parts) [110]. The originality of the toolbox lies in the fact that markers and muscles are independent sets from the osteoarticular model. Indeed, the correspondence between marker sets and muscle sets is made through the definition of geometrical locations on the body parts. The design or the modification of a musculoskeletal model is simplified thanks to this modularity. Following the same idea, some methods are defined as adaptable bricks. Testing new cost functions in the optimization schemes, changing performance criteria or creating alternative motion analysis methods can be done in a relatively easy way.

The analysis pipeline work as this: from an anthropometric based model, the geometric, inertial and muscular parameters are calibrated to fit the size and mass of the subject to be analyzed [9,30,67]. Then, from motion capture data (extracted from a c3d file thanks to the Biomechanical Toolkit [111]) the inverse kinematics step computes joint coordinates trajectories against time [16]. Then, joint torques are computed thanks to an inverse dynamics step [18]. To this end, external forces applied to the subject have to be known. They may be directly extracted from experimental data (as platform forces) or be estimated from motion data by using the equations of motion in an optimization scheme [101,107], as presented above. Last, muscle forces are estimated. The problem can be solved in classical fashion (optimization scheme) or with the MusIC method, as presented in the first focus of this chapter.

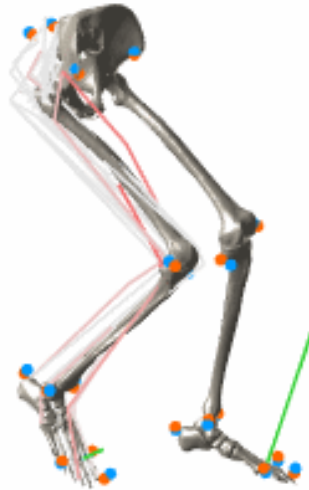


Figure 2.17 – A screenshot of an animation generated with CusToM. The GiBBON toolbox practical features are integrated into CusToM to obtain these renderings.

For a large set of musculoskeletal models and motion data, CusToM can easily perform all the analyzes described above. CusToM has been created as a modular tool to let the user being as free and autonomous as possible. The osteoarticular models, set of markers and set of muscles are defined as bricks customizable and adaptable with each other. Post processing features are also interesting to deal with experimentations with numerous trials. Last, recent developments on visualization (by including the GIBBON toolbox [112] in the distribution) enable the edition of nice animations, as shown in figure 2.17.

CONCLUSION

CusToM is still a fresh contribution to the musculoskeletal simulation community, but it is an exciting tool, accessible by many researchers that are not necessarily high-level developers. Even if the toolbox remains limited (open loop systems, limited library of models, ...), its open source nature is a real chance for its development in the next years. At term, CusToM may be used by non-expert as an analysis tool for preventive/corrective ergonomics without any limitation, since its graphical interface does not need any code to run and its model selection is simplified. The toolbox has been mainly initiated by Antoine Muller during his PhD thesis, even if I actively developed the core algorithms for inverse dynamics and I take credit for model assembly and muscle forces estimation features. Since its release, it is also the development tool used by three other PhD students I supervise (Pierre Puchaud, Louise Demestre and Claire Livet) and is currently used for analysis by several other students and colleagues (Olfa haj Mahmoud that is also under my supervision for example). We also propose doctoral courses on musculoskeletal modeling, using CusToM as a support software. It led me to develop several tutorials to be used with the toolbox.

RELATED PUBLICATIONS

[Muller et al. 2019b] Muller, A., Pontonnier, C., Puchaud P. & Dumont, G. (2019). CusToM: a Matlab toolbox for musculoskeletal simulation. Journal of Open Source Software 4.33: 1-3.

CONCLUSION

The work I presented in the current chapter is clearly motivated by the idea to democratize musculoskeletal simulation as a daily routine analysis tool. I'm not the first contributor of most of this work, and I can only thank the PhD students (Antoine Muller, Pierre Puchaud, Olfa haj Mahmoud, Claire Livet, Louise Demestre), the post-doc fellows (Diane Haering) I supervised this last 7 years for their work on the subject, as well as the other colleagues that participated to this work (Georges Dumont, Nicolas Bideau, Franck Multon, Pierre Plantard, Guillaume Nicolas, Coralie Germain). This is a collective effort and I am really proud of our achievements.

There is still a lot of room for research to be made, since democratizing musculoskeletal simulation for ergonomics studies is still a wish to accomplish. We evoked some of these issues in the last focuses, but we can summarize it here:

- First, the efficiency of such analysis methods for ergonomics relies strongly on computation time. Even if our results are interesting, we already reported that they are limited by the type of model they tackle (open loop arborescence). A real step forward would be to tackle any type of model with such methods, enabling more complex and accurate models to be used for assessment. As it has been explained earlier, this should pass by a deep adaptation of the methods, since dynamics of the system must be integrated into the interpolation scheme to solve concomitantly the inverse dynamics and the force estimation steps. I see here a real chance to adapt some relevant machine learning techniques to these challenges, as it has been proposed in [113]. I believe that a mix between model-based approaches and machine learning techniques such as neural networks or support vector machines may be relevant to limit the computation time and to learn from a limited amount of data some general rules to apply to any subject [71].
- Second, efficiency also relies on accuracy, asking for improvements in i) the accuracy of the models, ii) the realism of the motor control strategies applied to these models. Accuracy of the models is still subject to improvements through the development of original methods for scaling, especially at the muscle level. Force-based assessment of the work conditions is not developed at all and may benefit from accurate musculoskeletal models to be realized systematically. Again, machine learning techniques are relevant to tackle this issue, as it is proposed in the last chapter of this manuscript. The realism of the motor control is also subject to questions. Classical cost functions used in muscle forces estimation are not adapted to all the motions to study and are quite bad at estimating co-contraction. Alternative control strategies were evaluated (metabolic cost, stiffness-based cost functions [114,115]) but there is a need of development of new and adapted control strategies to enhance this part of the simulations.
- Last, there is still a need to better handle the inputs of the analysis. It implies to have easily available data (IMU, depth cameras), with a relevant pre-processing (drift [116], STA [64,117] ...), enabling a similar level of analysis as gold standard input data (optoelectronic motion capture). Such developments may also benefit from data correction and completion, as we already proposed it for Kinect.

In addition to these scientific issues, these works open several application perspectives that are extensively developed in the last chapter (5) of this manuscript.

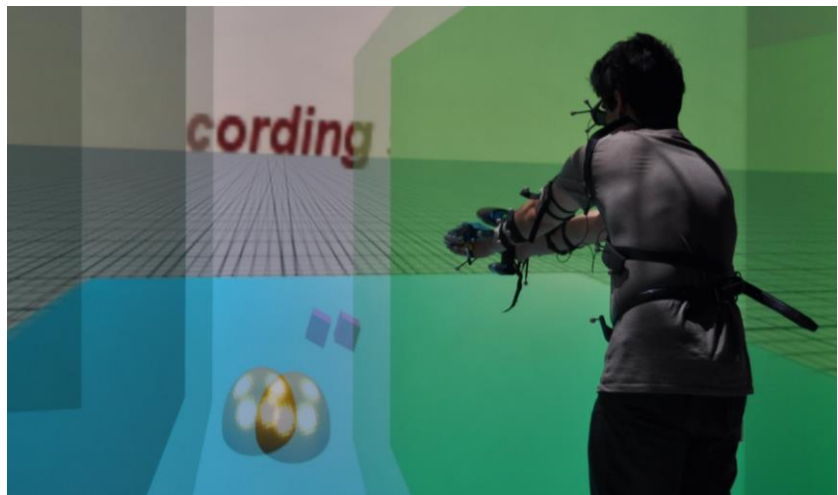
I made the choice to no present all our work related to musculoskeletal simulation to be focused on issues specific to ergonomics. To be more exhaustive, I should mention that we conducted a very comprehensive work on throwing motions during the PhD work of Ana Lucia Cruz Ruiz, that I co-supervised with Georges Dumont within the frame of the ENTRACTE (ANR CONTINT) project between 2013 and 2016. The idea was to generate a low-level representation of the motor control involved in such motions (throwing a ball over the

shoulder) to synthesize motions in direct dynamics for musculoskeletal models. The link with ergonomics is not direct, however this work was an important step for us to extend our knowledge on motor control and motion analysis and synthesis. Moreover, it was the first application made from the CusToM library, that was not called like this at this stage. This work has been published in several articles [118,119,120].

At last, I also conducted a thorough analysis of simulated meat cutting tasks during my postdoctoral stay in Aalborg. This work was conducted with the AnyBody software and was the opportunity to demonstrate the usability of such software for an analysis of a complex task involving large force exertion. I particularly developed during this stay a validation by trend analysis, considering comparison of muscle forces/activation between work situations to be a relevant way to use musculoskeletal models for ergonomics [13]. This work has been fundamental in my research background since it let me acquire a real expertise with the AnyBody software and the fundamental algorithmic developments related to it.

E

fficient virtual reality for ergonomics



End-user in interaction with a collaborative virtual environment for ergonomics
Nguyen, H. et al. (2017). **VR-based Operating Modes and Metaphors for Collaborative Ergonomic Design of Industrial Workstations**. *Journal on Multimodal User Interfaces*

INTRODUCTION

As stated in introduction of this document, virtual reality (VR) is an appealing technology to develop controlled and modifiable environments in interaction with multiple users. This is particularly true for sports, rehabilitation or ergonomics applications. VR is already used as a support for products [121,122] or workstations design [10,123]. Indeed, virtual prototyping - the act of evaluating a product by simulating its behavior and its interactions with humans and/or other components - has become increasingly relevant, especially for evaluating assembly tasks. At this point, the use VR becomes quite natural to evaluate the functionalities or ergonomic features of workstations [124,125] since it is more cost-effective and easier to edit a digital mock-up (DMU) than a real mock-up. The display and interaction modalities may differ from one application to one other. Classically, CAVE (large immersive rooms) were the classical way to display the workstation to the final user, but the recent development of efficient Head-Mounted Displays (HMD) – see Oculus Rift®, HTC Vive® systems for example, led to several developments on these display tools. The interaction may also differ depending on the application. Generic interaction devices may be used for low forces exertion (tracked joysticks for example), whereas for tasks involving force exertion haptic devices may be preferred.

Considering the following scheme that we proposed in one of our papers [13], a collaborative ergonomic design session should provide i) high fidelity systems leading to reliable and transferable conclusions in terms of physical risk factors assessments ii) high usability systems leading to a flexible interaction between different actors of the design and the design itself.

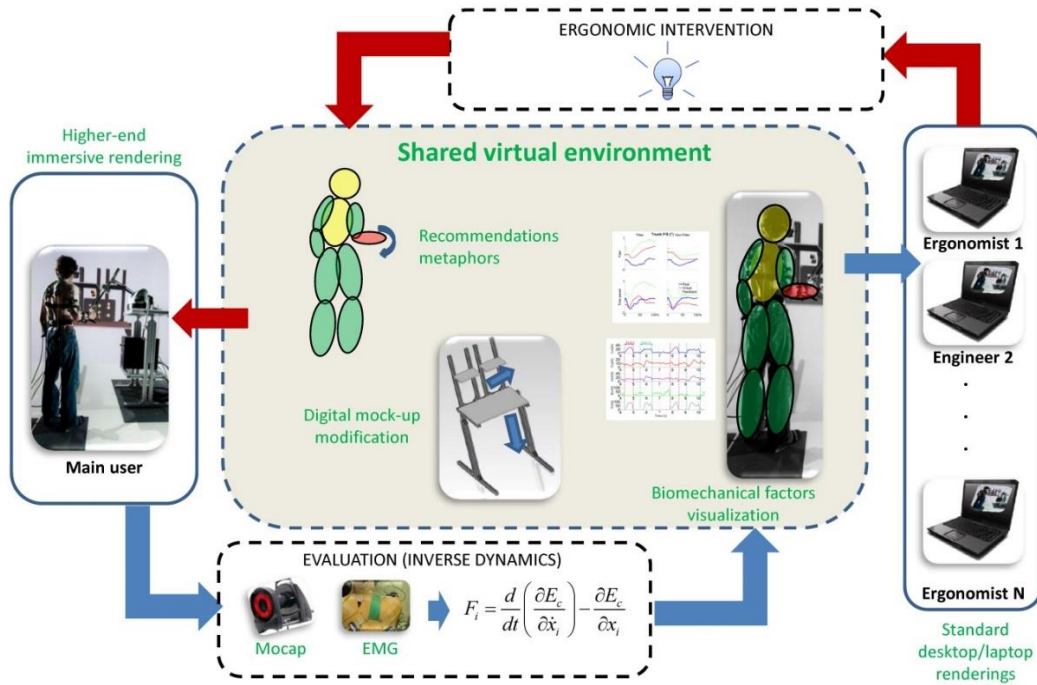


Figure 3.1. A very first approach of collaborative virtual environment for ergonomics. One can notice at the bottom of the figure the box containing most of the motion analysis methods developed and proposed in the previous chapter.

The first major question concerns the reliability and transferability of the assessment in virtual reality and its conformity with the real world. If we consider assessing physical risk factors in virtual reality, it is necessary to

ensure that the motions and forces exerted by the user in a virtual environment to perform a virtualized task are comparable to the ones he would develop for real. Moreover, there is a necessity to ensure that motor control and sensory feedback are comparable, since comparable forces and motions may be realized in many ways by a human subject. All these questions can be summarized by a concept that we can call the “biomechanical fidelity” (or biofidelity) of the environment. Considering the classical definition of the fidelity - the objective degree of exactness with which real-world experiences and effects are reproduced by a computing system [126], the biomechanical fidelity combines interaction, simulation, and visualization features to define the exactness with which the virtual environment makes the subjects react in terms of motion, forces and control. In ergonomics, designers and industrials tend to minimize the cost of the simulator in virtualizing most of the workstation features. Moreover, the most-cost effective approach is to define several types of interactions with a generic device, such as a joystick or a haptic arm, to limit the development costs. These choices make the virtual environment being quite far from the real one. Thus, it seems crucial to find objective and subjective metrics that enable comparisons between real and virtual situations. The biomechanical fidelity concept is extensively developed as the first topic of this chapter.

The second major issue is the question of the usability of such systems. Virtual environments will be efficient for workstation design and ergonomics only if the different actors involved in the design process, i.e. design engineers, ergonomists and final users (industrial workers) can interact with each other and with the scene in a convenient way. Indeed, the design engineer guarantees the process constraints to be fulfilled while the ergonomist guarantees the respect of the ergonomic constraints. At last the final user guarantees that the workstation is adapted to his morphological and physical features according to the task to complete and has a role to play in the final usability of the workstation. This question is complex since it asks to provide interaction tools that differs from one user to another and that must be adapted to multiple rendering media. It also have to cover all the possible need of constraint expressions that could arise from such design. Therefore, we focused on the development of virtual environments enabling an interaction between different actors using different media for ergonomics design sessions. This is the second topic developed in this chapter.

I first worked on the virtual workstation design setups just after my stay in Aalborg university in 2012. At this stage, I had the opportunity to collaborate with my colleagues from Aalborg Afshin Samani (associate professor, ergonomics) and Pascal Madeleine (professor, ergonomics) within the VISIONAIR project (FP7 INFRA, led by Pr. Frédéric Noël [127]) – this project was dedicated to provide high level virtual reality infrastructures to European researchers. This collaboration led to the first contribution developed in the current chapter on biomechanical fidelity of virtual environments. I also had the opportunity to work with my colleague Thierry Duval (professor at IMT Atlantique). Thierry is a specialist of collaborative virtual environments and developed with some of his students a framework for collaboration in virtual environments called Collaviz [128]. I particularly collaborated to the PhD of Huyen Nguyen that Thierry supervised in the years 2011-2014. More recently, we extended our work on biomechanical fidelity to several other tasks with the thesis of Simon Hilt (2017-), co-supervised with Georges Dumont.

TOPIC 1: BIOMECHANICAL FIDELITY OF VIRTUAL ENVIRONMENTS

CONTEXT & OBJECTIVE

Though ergonomic design and evaluations have already been performed in virtual reality at a postural level, it has been done with weak guarantees of transferability, which can be defined as the degree to which the ergonomic conclusions in virtual environments are valid in the real world. Indeed, the transferability of the results is deeply related to the level of fidelity of the simulator – the extent to which a Virtual Environment (VE) and interactions with it are indistinguishable from a real environment. Fidelity of VE has been described in literature as a composite feature of three main dimensions: simulation, display and interaction fidelity [129,130]. These dimensions are not enough to fully characterize fidelity in the case of ergonomic design applications. In such applications, it is mandatory to understand how human motor control is affected by physical, sensorial and cognitive differences between simulation and reality. Conclusions made at the end of an ergonomic design session must be transferable to the real world with the same descriptive level of ergonomic analysis. It is therefore necessary to define a new dimension in fidelity, which I refer to as Biomechanical Fidelity (BF). I propose to define the biomechanical fidelity as the degree of similarity between motions, forces, and tasks realized in real and virtual environments at a biomechanical level (the level used to assess physical risk factors in ergonomics). A high biomechanical fidelity rating would ensure that conclusions and changes applied to the virtual workstation are transferable to the real world. However, characterizing biomechanical fidelity is not straightforward and requires addressing multiple scientific challenges.

Biomechanical fidelity can be seen as a multilevel scale of description associated to virtual applications. Indeed, the biomechanical fidelity expresses the idea that biomechanical quantities are consistent between a real and virtual counterpart of a given activity. In fact, good postural fidelity may be enough for non-strenuous but repetitive tasks whereas tasks asking for a high level of force may have to be assessed at muscular level and therefore ask for high biomechanical fidelity at this descriptive level.

Figure 3.2. depicts a classification of the descriptive levels to be assessed to ensure a sufficient BF. 3 main levels corresponding to classical biomechanical quantities are identified: kinematics, dynamics and muscular. For each of these levels, objective assessments of the similarity between a real activity and its virtual counterpart are proposed.

For example, assessing the biomechanical fidelity at a kinematics level of sorting tasks will consist in recording motion to compute kinematics (postures and joint angles) in real and virtual.

The comparison of the quantities can be done globally (using classical ergonomic criteria, e.g. RULA or REBA scores), or at a more specific level (e.g. comparing joint angles trajectories). A more complex analysis can be driven through the challenge of motor control theories (in our example: uncontrolled manifold on a goal such as balance).

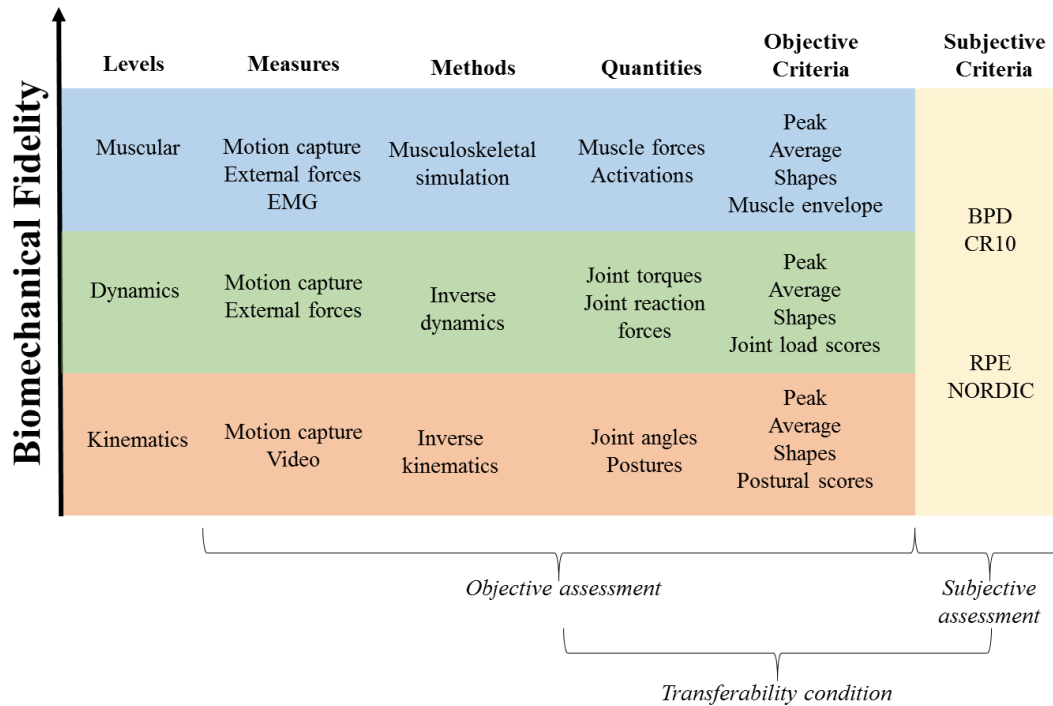


Figure 3.2. Multilevel classification for Biomechanical Fidelity and objective and subjective assessment suggestions.

A perfectly biomechanically faithful virtual application will in all these analyses give similar quantitative results as the real application. However, the virtual version of the task will give quite different quantitative results, since the interaction, sensory feedback...will be different. Thus, it is necessary to apprehend the validation differently.

Several prior works attended to tackle this problem by comparing real and virtual setups thanks to biomechanical quantities. We can cite for example the work of Ma et al. that worked specifically on simulated drilling tasks, showing clear differences in terms of postures and discomfort between real and virtual setups [131,132]. These results were inspiring for us since they mostly assessed the key postures of the motion. We wanted to extend such works to the complete motion of the subject during the task.

This is the topic of the current section, in which are presented several works developed during my first years as an associate professor and in collaboration with my colleagues of Aalborg, Afshin Samani and Pascal Madeleine. We particularly collaborated within the frame of the VISIONAIR project, in which we proposed an exploratory project that led to the following setup.

AN EXPERIMENTAL SETUP

To compare simulated tasks at a biomechanical level in real and virtual environments, we chose a task that was simple enough to be reproduced in an immersive room with generic devices, and complex enough to authorize experimental condition variations. Indeed, changing the work environment and following the trends of the biomechanical indicators regarding these trends is a relevant way to enhance work conditions.

The chosen task was a simplified sorting/assembly task, including several elementary operations and conditions that can be found in a real industrial process: target reaching, object manipulation, piece sorting, standing posture, and repetitive motion. These specific features are well-known to be involved in the appearance of WMSDs [1]. The task was performed in three environments: RE, VE, and VE with force feedback (VEF). VEF was proposed to the subjects in an additional session. The task was somewhat different from the other ones, as haptic device articular limitations required several additional manipulations during the task.

An overview of the experimental setup is shown in Figure 3.3. The RE consisted of a workspace including a storage and a disposal zone, a holed box, and twelve wooden objects. The holed box was located on a work plan set at elbow height (recommended for light work [133]) and the storage and disposal zones were located 40 cm above the table surface and 16 cm to the left and right of the center of the holed box, respectively. The holed box had several holes with different cross-sectional contours which could accept some of the objects (“fitters”), while the other objects (“non-fitters”) could not pass through any of the holes.

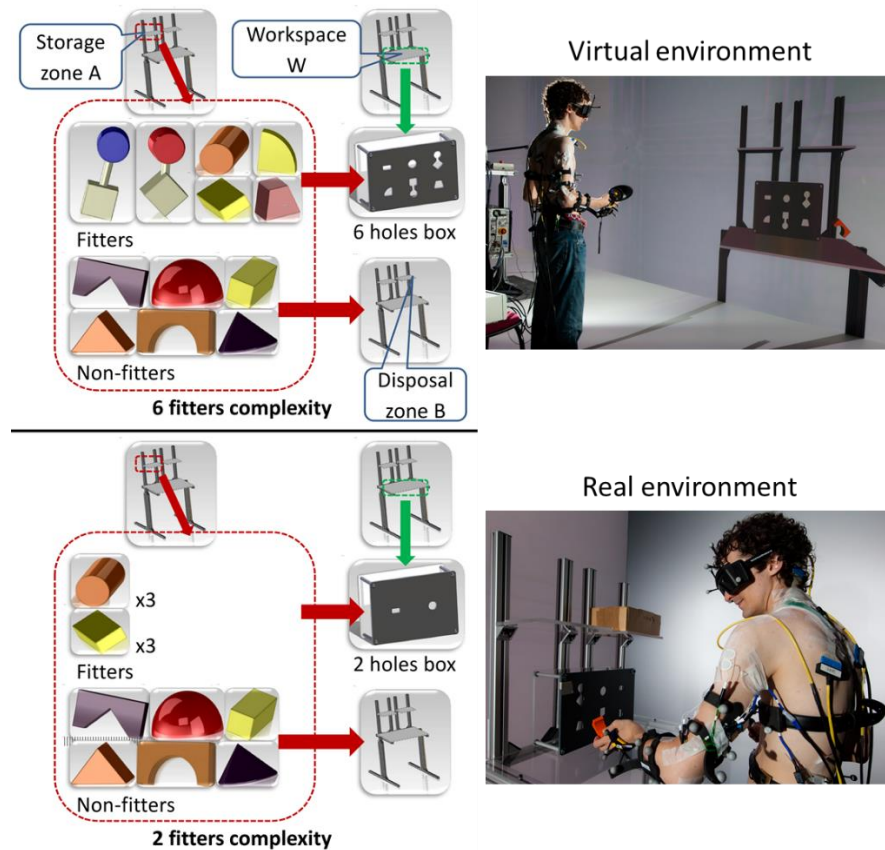


Figure 3.3. Simulated assembly tasks performed in real and virtual environments. The task consists in placing sorting objects with a holed box. 12 wooden objects taken from the disposal zone A must be sorted. 6 objects are fitting the holes and 6 others must be placed in disposal zone B. Experimental conditions changed in two ways: task timing and complexity.

During the study, the subject stood in front of the table and, after receiving a verbal let-go signal, grabbed an object from the storage zone with his right hand. The subject had to pass fitters through the appropriate holes in the holed box while non-fitters were placed in the disposal zone. There were six fitters and six non-fitters in each trial. Each piece weighed about 40 grams.

The VE was designed to precisely mimic the RE. The 3D representations of the workstation and of the holed box were derived from the DMUs used to fabricate the real environment. The virtual table height was also visually adjusted with respect to the subject's elbow height. The pipeline leading to both manufacturing of the real work plan and the preparation of the digital one for the experimentation has been extensively explained in [13] and can be summarized as shown in figure 3.4.

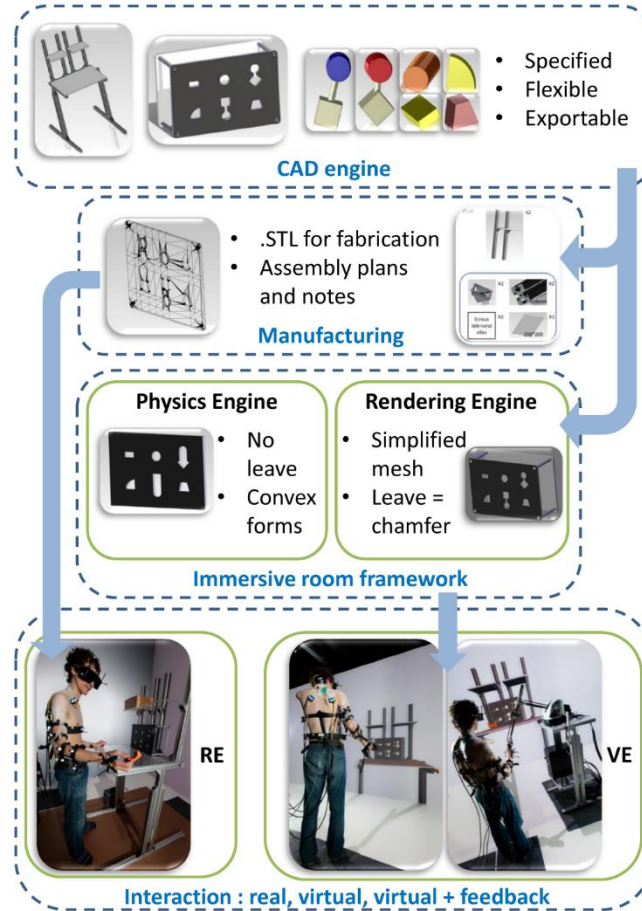


Figure 3.4. Numerical pipeline leading to the development of the digital and real workplan. A particular attention was paid to the physical and rendering issues, leading to several simplifications. Indeed, make the scene able to run in real time with collisions and complex fitting issues was challenging. An initial study proposed in [13] showed that neither physical or rendering simplifications did diminish the fidelity rated by the subjects.

The virtual system used a high-resolution stereoscopic immersion room including a wall and a floor (vertical wall: 9.6mx3.1m, 6240x2016 pixels, eight Barco NW12 projectors, BARCO Inc., USA; floor: 9.6mx2.88m, 3500x1050 pixels, three Barco Galaxy 7 projectors, BARCO Inc., USA). Three-dimensional glasses (ActiveEyes-Pro, Volfoni, SAS, France) tracked with a 360° tracking system equipped with 16 ART infra-red cameras (Advanced Real Time Tracking GmbH, Germany) were used to adapt the simulation to the user point-of-view. Only one object appeared on the storage shelf at a time and the subject had to grab the object using a wireless interaction device (Flystick2, Advanced Real Time Tracking GmbH, Germany) co-localized with the VE.

To compare the simulated assembly tasks realized in real and virtual environments, we led an experimentation campaign based on the experimental protocol described above.

We recruited sixteen male subject that participated to the study after giving their informed consent. They were all novices in Virtual Reality (Average experience of 1.4 ± 0.5 on a 5-point scale).

Each subject realized the task described in the previous section. Different within-subject factors were investigated in order to understand the influence of the VE and VEF on performance. Two cases of complexity of the task were proposed: a case with only two types of fitters (cylinder and parallelepiped) and a case with six types of fitters (see Figure 2). The timing regime factor also had two levels: “as fast as possible”, where the subject did not take any break between pieces, and “time-constrained”, where the subject waited for a sound signal before taking a new piece, which occurred every 10 seconds. For each environment, the complexity and timing regime were randomly ordered to prevent cross-over effects. The different environments were randomly balanced to prevent task-learning effects (RE, VE and VEF).

During the task realization, orientations of the trunk and the upper limb segments were tracked using six dedicated AR-Tracking targets, sampled at a 60 Hz frame rate: lower trunk, upper trunk, head (glasses), right arm, forearm, and hand. Muscle activities were recorded along the kinematical chain. Five bipolar channels were used to collect electromyographic (EMG) signals from the Erector Spinae (ES, back extensor), Deltoideus Medialis (DltMed, shoulder abductor), Biceps Brachii (Bscps, forearm supinator and elbow flexor), Triceps Long Head (Trcps, elbow extensor and shoulder stabilizer) and Flexor carpi ulnaris (FCU, wrist flexor and adductor) with bipolar surface electrodes (Neuroline 720, Ambu, Denmark). Bipolar surface electrodes were aligned (inter-electrodes distance: 2 cm) on abraded ethanol-cleaned skin along the direction of the muscle fibers. Bipolar electrodes were placed with respect to anatomical landmarks. Upper-middle trapezius activity was recorded thanks to a semi-disposable adhesive grid of 64 electrodes (LISiN-Spes Medica, Italy, model ELSCH064R3S). The EMG signals were amplified 2000 times (64-channel surface EMG amplifier, SEA64EMG-USB, LISiN-OT Bioelectronica, Torino, Italy), band-pass filtered [5-500 Hz] and sampled at 2048 Hz (National Instrument, 12 bits acquisition board, Austin, USA).

FIDELITY ASSESSMENT

From this experimentation, we ran 3 main analyses that were published in different articles [134,135,136].

First, we focused on a comparison of indicators of discomfort computed in real and virtual environment. For this approach, after ensuring through a first statistical approach that it had no influence on the other results, we discarded the VEF trials that were incomplete (only 10 from 16 subjects did this part of the experiment). This first approach was simple and a real assessment of the capacity of the virtual setup to provide similar conclusions as the real setup in terms of physical risk factors.

Therefore, we computed several indicators of discomfort from the recorded data: we computed a RULA (Rapid Upper Limb Assessment) score from the tracked orientations of the segments. The RULA score represents a good indicator of postural discomfort [4]. We also computed Averaged Muscle Activations (AMAs) that are simply an averaged measure of the activity for a considered muscle. AMAs give a good overview of the muscle load during the task and are used to compare similar tasks under different conditions [137]. EMG activation profiles were normalized with activation levels obtained from a reference task, to get comparable results across subjects. For the “as fast as possible” condition, the elapsed time between the beginning and the end of the task was recorded as Total Task Time (TTT), as task duration affects fatigue and discomfort of the subjects and vice-versa. Finally, subjective indicators were reported during the experimentation. After each trial, subjects were invited to report their Rated Perceived Exertion (RPE), based on CR-10 Borg’s scale [138] and indicating

the perceived level of discomfort (0 – no discomfort, 10 - highly uncomfortable). At the end of the experimentation, subjects answered a short questionnaire assessing the difficulty of the task in real and virtual, and fidelity of the virtual environment.

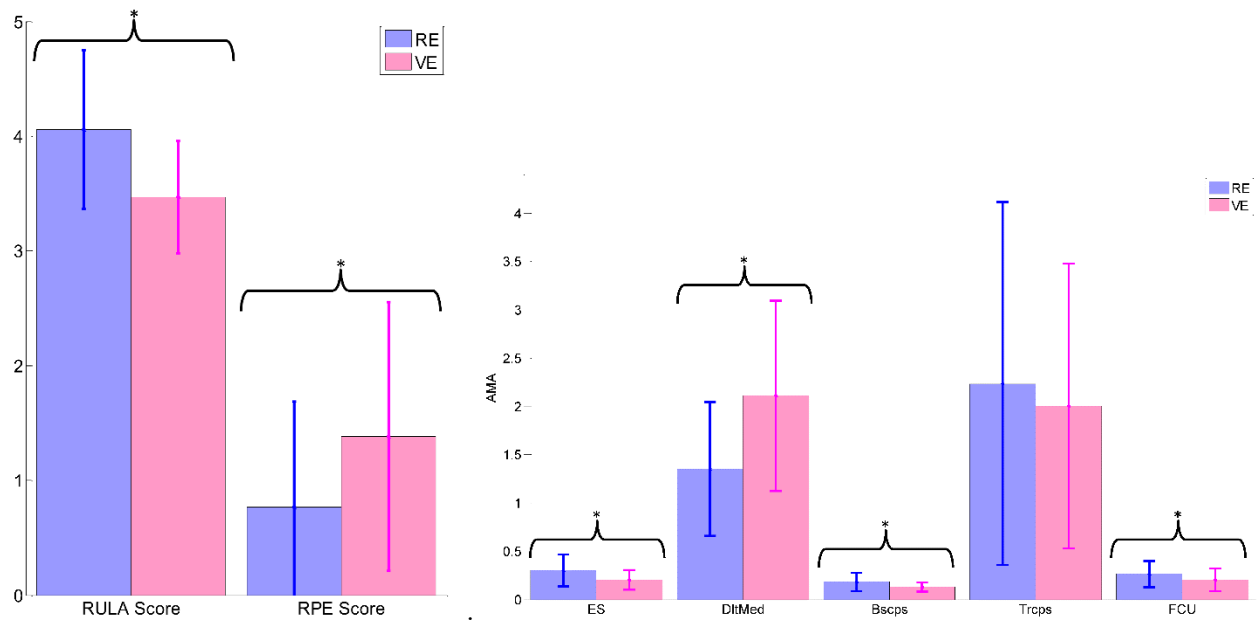


Figure 3.5. RULA, RPE and AMAs scores comparison between real and virtual environments. The statistical analysis revealed different activation levels, a lower postural constraint and a higher perceived discomfort for the virtual environment in comparison to the real one.

Results were statistically processed using ANOVA and post-hoc tests (Tuckey's HSD). Interaction type, Timing regime and Complexity were introduced as independent factors and dependent variables were the objective and subjective indicators (RULA score, AMAs and RPE score). A specific ANOVA was calculated for TTT, including only the interaction type and the complexity. The level of confidence was set to $p < 0.05$. Correlations between indicators obtained from RE and VE trials were investigated using a linear regression. The correlation coefficient r was computed for each indicator with a level of confidence set to $p < 0.05$. Sample sign tests were performed to determine differences between RE and VE for questionnaire results.

The results of this study showed several interesting results that we summarized here.

First, a statistical difference between RULA scores were found between real and virtual environments. This must be related to the statistical difference reported for the RPE. This is a fundamental point since postures were less comfortable in virtual than in real (see figure 3.5.) whereas the subjects reported more discomfort in virtual than in real. In ergonomics, a classical way to consider the subjective and objective indicators is to consider they are correlated [139]. This is not the case here and asks for questions in the way the subjects were disturbed by the virtual environment. Cognitive charge as well as sensory feedback were different, and it is classical to consider that it leads to different motor control strategies. The most obvious reason of these difference is the interaction itself, that was quite different between both environments. However, the previous remark about motor control and sensory feedback seems a valid hypothesis to explain the contradiction between the objective and subjective ratings.

At the same time, the correlation between scores obtained in real and virtual environments for similar conditions was positive for many indicators, as shown in figure 3.6. It showed that despite the differences reported above between the real and the virtual tasks, the evolution of these scores regarding the experimental conditions (complexity, timing regime) were consistent between both environments. This is a major observation since it validates, at least for this type of task/motion, the usage of such generic interaction and display devices as a relevant assessment system for preventive ergonomics.

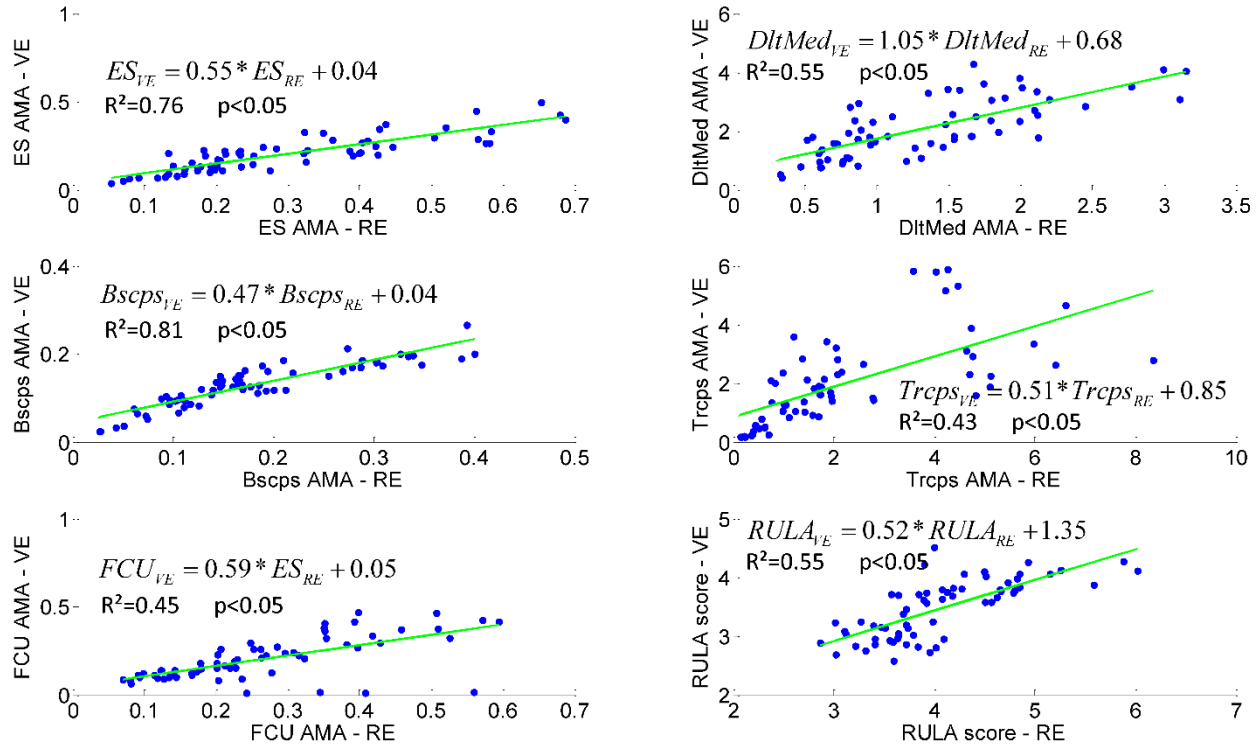


Figure 3.6. Correlation between indicators measured in real and virtual environments for similar conditions (timing regime and complexity). All trials of all subjects were used to compute the correlation.

These two results implied several additional research questions. These questions were addressed in two additional papers.

The first issue that was addressed can be summarized like this: was the variability of the motor control response higher from one environment to one other or from one subject to one other? A classical assumption in ergonomics to compare two work conditions is that if the intra-subject variability across the conditions is greater than the inter-subject variability within a task, the two conditions will be seen as different working conditions [140,141]. Therefore, along with such an approach one can apply methods such as cross-correlation and normalized mutual information (NMI) to quantify the similarity (the opposite of the concept of variability) of the biomechanical response of subjects in different conditions and compare the inter- and intra-subject similarity [142]. Considering this, we assumed that the intra-subject similarity of biomechanical response across real and virtual environments is comparable with the inter-subject similarity within the real environment.

More specifically, we applied this method to the 3 joint angle trajectories of the shoulder and the spatial muscle activity of the upper-middle trapezius, recorded with a semi-disposable adhesive grid of 64 electrodes. We

measured the intra-similarity of these quantities between real (RE), virtual (VE), and virtual plus force feedback (VEF) environments, and the inter-subject similarity of these quantities for the real environment.

Results showed that even if VE preserved better the kinematic trajectories than VEF regarding real trajectories, trapezius activity patterns were more similar between VEF and RE than VE and RE. This result is of interest since it indicates that even if the shoulder kinematics was better reproduced in VE, the lack of force feedback changed the muscle activity. A similar contrast between EMG and kinematic patterns has previously been observed and explained by the notion of complexity trade-offs between the macroscopic (kinematics) and microscopic (EMG) levels of a control system [143].

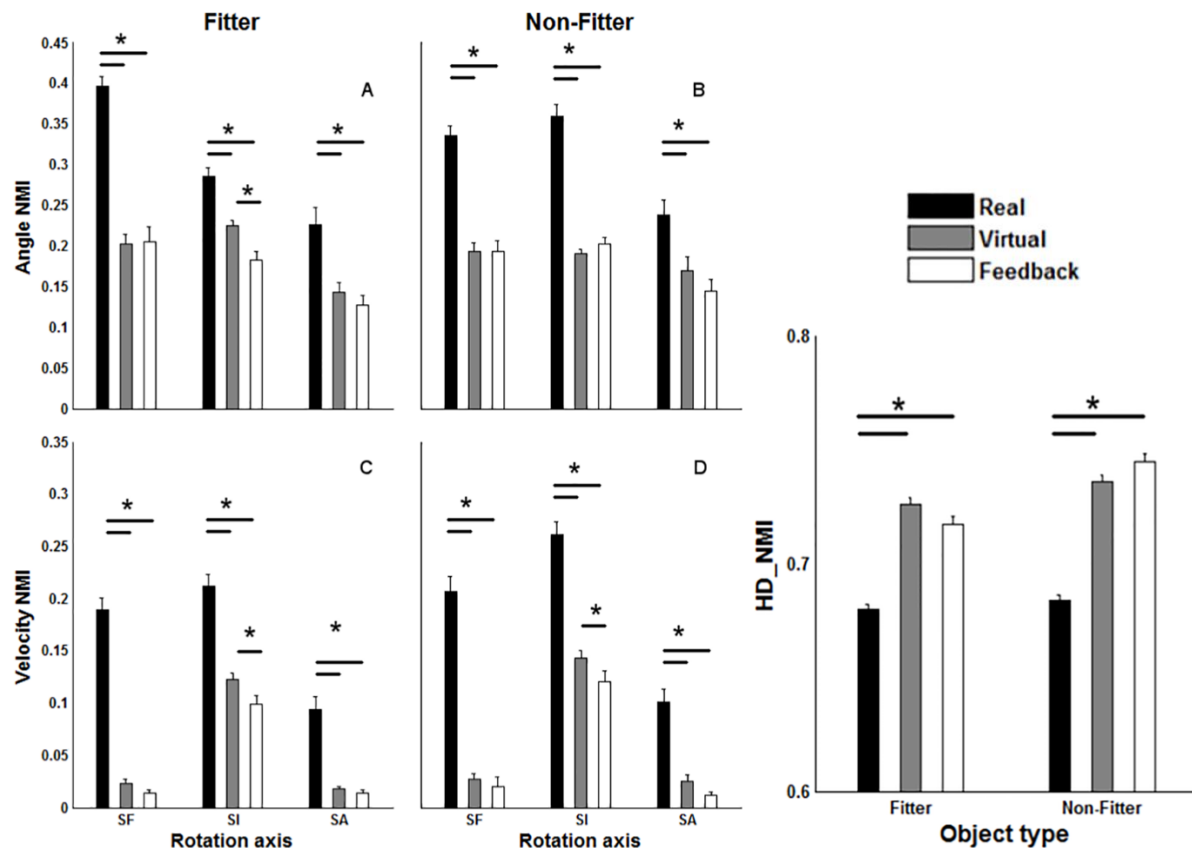


Figure 3.7. Kinematical pattern intra-subject similarity is lower than the inter-subject one. On the contrary, muscle activation pattern intra-subject similarity is higher than the inter-subject one.

Finally, contrary to our assumption, we found that the kinematic trajectories were more similar between the participants performing the task in RE compared with the similarity of kinematic trajectories belonging to a single participant working in different environments. This is an important finding since a reliable evaluation of the biomechanics in VR environments requires that the intra-subject similarity of the biomechanical responses across platforms is comparable with the inter-subject similarity of the biomechanical responses of the real work platform. A similar approach has previously been applied in ergonomics studies where the ratio between inter- and intra-subject variability has been used to contrast different working conditions [142,144]. It seems unlikely that the gradual adaptation of the participants to the task would result in a systematic bias to our results at the within-subject level because the participants performed the task in a randomized balanced order across the platforms. Additionally, if the adaptation level is assumed to be different across subjects, the between-subject

variance increases and, in turn, results in lower inter-subject similarity. This supports our interpretation even further. Muscle pattern similarity showed the opposite trend, since intra-subject similarity was higher from one platform to one other than inter-subject similarity on the real platform.

These results qualified a bit the results of the first analysis since even if the global criteria evaluated in the first study showed relatively positive correlation between platforms, the detailed analysis performed here showed large differences between environments in terms of angle trajectories and muscle activation patterns.

Another issue we wanted to further investigate was the contradiction reported between RPE and RULA in the initial study [132]. Indeed, we wanted to understand why the subject experienced more discomfort with less postural constraint. To this end, we studied the stabilization of the upper body during the realization of the task between RE and VE. We used the Uncontrolled Manifold Theory (UCM) [145] to understand how was controlled the stabilization of the center of mass of the upper body during the task. Thanks to this motor control theory, we decomposed the contribution of joint angles of the upper body into a goal equivalent (GE) and non-goal equivalent (NGE) component, representing how much the different joint angles are used to stabilize the upper body. The ratio between GE and NGE is a good representation of that: the higher it is, the higher is the stabilization.

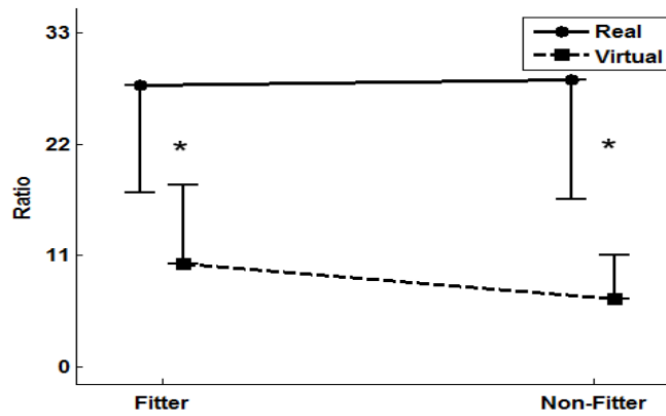


Figure 3.8. GE/NGE ratio between real and virtual environments for fitter and non-fitter objects. The ratio is significantly lower in VE than in RE, showing a less stabilized center of mass of the upper body in VE than in RE.

Computing this quantity for RE and VE, results showed in both environment a higher GE than NGE. It is logical since stability is a core motor control task that must be always fulfilled. A higher ratio in RE compared with VE indicates that the subject performed the task in RE while they had a more stable upper body (i.e. CM) compared with VE (see figure 3.8.). This ratio could be used as index of performance in VE when it is being compared to the real ones. It is conceivable that the visual feedback is changed in VE and visual feedback is known to be crucial in movement planning and control [146]. Thus, the differences between VE and RE platform can be related to a manipulated visual interface in VE. Even if this interpretation may be contested in many ways, the lack of stability in VE may be a relevant explanation of the contradictory results between RULA and RPE. Indeed, even if postures were less constraining in VE than in RE, the perceived discomfort was higher: the lack of stability of the subject may have produced this perception.

CONCLUSION

Finally, the most important characteristic of a virtual environment dedicated to preventive ergonomics is its ability to make the results transferable. A good way to ensure that is to compare the evolution (or trends) of the biomechanical quantities with regard to changes in the activity instead of absolute values. For the type of tasks we just presented (sorting/assembly tasks) it can be assessing the joint angle ranges with regard to the workplan height and compare real and virtual results. That is the sense of what we called the biomechanical fidelity at the beginning of this section.

Moreover, disturbed sensory feedback in VR may have a negative impact and lead to bias in the assessment as we already observed in some of the results we had. Therefore, an additional necessary condition of transferability concerns the correlation between objective and subjective ergonomic criteria. The reliability of subjective criteria (Rate of Perceived Exertion, Body Part Discomfort...) is based on the correlation with objective ones, then similar correlation has to be found in a virtual setup aimed at performing ergonomics.

To conclude, the biomechanical fidelity can be seen as a key to enhance the usability of virtual environments for preventive ergonomics. The work we developed here extensively studied sorting/assembly tasks and has to be taken with caution since it deals with a specific rendering/interaction setup, as well as a specific simulated task. Transferability of the results must also be assessed with regard to the adaptation of the subject to the task. These differences in motor control adaptation may have to be assessed on large cohorts and on long term studies. Within the frame of the PhD work of Simon Hilt, currently supervised by Georges Dumont and me, we are trying to extend the work we made on sorting/assembly tasks to new ones, using alternative rendering setups. In particular, we worked on pick-and-place tasks [147] and we are currently exploring virtual hammering with a similar approach to the one developed above: assessing biomechanical fidelity as a key for the transferability of the ergonomic assessment results from virtual to real.

RELATED PUBLICATIONS:

- [Pontonnier et al. 2014a]** Pontonnier, C., Dumont, G., Samani, A., Madeleine, P., & Badawi, M. (2014). Designing and evaluating a workstation in real and virtual environment: toward virtual reality based ergonomic design sessions. *Journal on Multimodal User Interfaces*, 8(2), 199-208.
- [Pontonnier et al. 2014c]** Pontonnier, C., Samani, A., Badawi, M., Madeleine, P., & Dumont, G. (2014). Assessing the ability of a vr-based assembly task simulation to evaluate physical risk factors. *IEEE transactions on visualization and computer graphics*, 20(5), 664-674.
- [Samani et al. 2015a]** Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015). Shoulder kinematics and spatial pattern of trapezius electromyographic activity in real and virtual environments. *PLOS one*, 10(3), e0116211.
- [Samani et al. 2015b]** Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015). Kinematic synergy in a real and a virtual simulated assembly task. In *Proceedings 19th Triennial Congress of the IEA* (Vol. 9, p. 14).
- [Hilt et al. 2017]** Hilt, S., Pontonnier, C., & Dumont, G. (2017). Model Based Compensation for Low Mass Objects Haptic Manipulation in Virtual Environments. In *International Conference on Virtual Reality and Augmented Reality, Lecture Notes in Computer Sciences 10700*, (pp. 87-101)

TOPIC 2: COLLABORATIVE VIRTUAL ENVIRONMENTS FOR ERGONOMICS

CONTEXT & OBJECTIVE

After we first established a short review of studies dealing with VR for preventive ergonomics, we identified a real lack in virtual environments able to provide reliable interaction techniques for the different actors of a workstation design in virtual environments working on a shared representation of this workstation. In a paper we published in 2013 [148], we went to the following framework as relevant for such an approach:

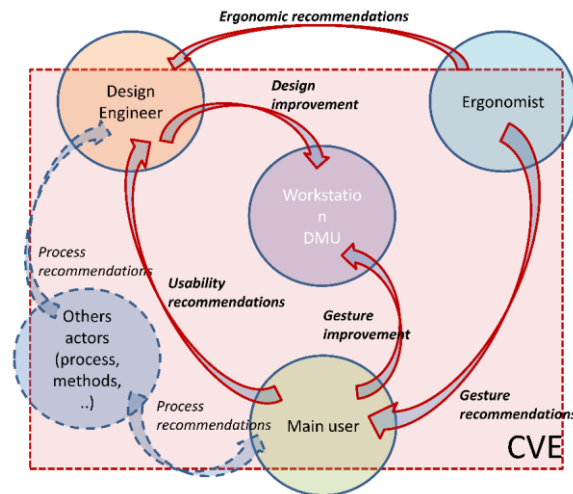


Figure 3.9. A relevant collaborative virtual environment setup enabling the interaction between a end-user, a design engineer and an ergonomist.

The virtual environment is shared among 3 types of users, that are the end user (that will eventually use the prototyped workstation in real conditions) and ergonomist (guaranteeing the ergonomic constraints to be respected) and the design engineer (guaranteeing the process constraints to be respected).

The development of specific tools based on collaborative virtual environments (CVE) is a serious way to enable such interactions. CVE exhibit a great potential of application in numerous domains: scientific visualization, product design, rehabilitation and many more. Using a CVE for ergonomic purposes is very compelling. Indeed, a CVE can be considered as a major tool for workstation design, as it has the potential to enable real-time interactions between all the actors involved in the design process. This statement is true only if the CVE is properly designed.

The following section explains the design we proposed for our dedicated CVE and its evaluation in terms of collaborative design, that I mostly developed from 2011 to 2014, and in collaboration with Thierry Duval within the thesis of Huyen NGuyen.

CVE ARCHITECTURE

On the basis of the scheme above, we developed with our colleague Thierry Duval several metaphors and tools to enable the interaction between the actors. These developments have been published in two conference

articles [148,149]. The idea was mostly to find relevant ways to enable collaboration with simple and clear metaphors. All of these features were developed in the Collaviz framework [128] and tested in the immersia immersive room [150].

End-user/ergonomist interaction architecture

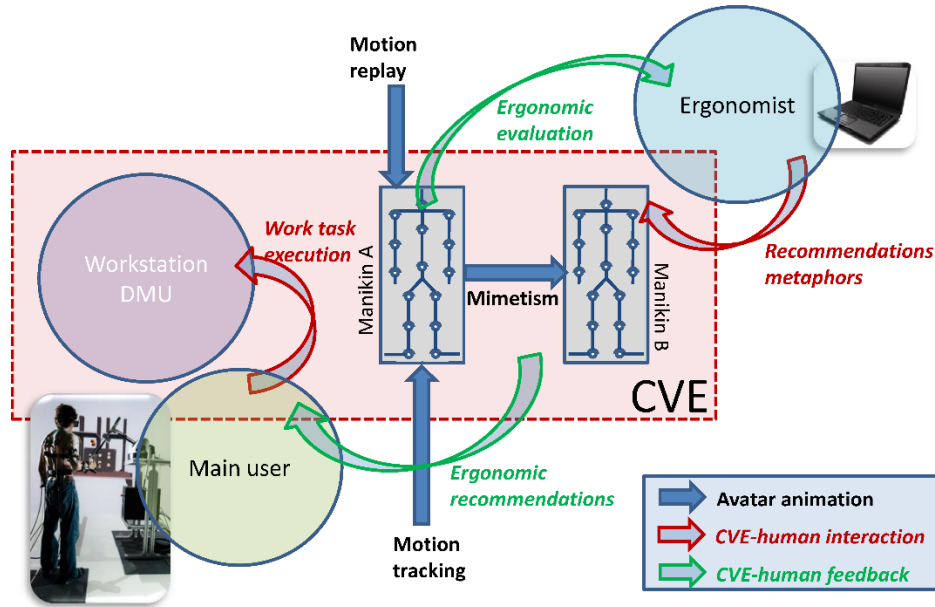


Figure 3.10. An interaction architecture between an ergonomist and an end-user in a collaborative virtual environment dedicated to preventive ergonomics.

First, the end-user and the ergonomist need to communicate. The end-user must be able to realize the virtualized task and receive advices/recommendations from the ergonomist. The ergonomist must be able to visualize the workstation, analyse the motion of the end-user, and propose recommendations to the end-user (and the design engineer to modify the DMU).

In order to enable this communication and interaction between these actors, we proposed the architecture presented figure 3.10. Two similar virtual manikins represented in the virtual environment and seen by both users are proposed. The manikin A is used as a main manikin and can be animated either directly from the motion tracking of the end-user or in replaying a previously recorded motion. Manikin B that can be considered as a ghost manikin, can either mimic the manikin A or be manipulated by the ergonomist. Actually, manikin B is mimicking manikin A most of the time, but the ergonomist has the opportunity to stop this mimetic feature to indicate whatever he needs on the manikin. The combination of these animation modes define several work modes for the application:

Active-Passive: Manikin A in direct tracking and manikin B in mimetic. This mode is mostly used by the ergonomist to observe, analyse and record the current work task;

Active-active: Manikin A in direct tracking and manikin B manipulated by the ergonomist. This mode is used for a direct evaluation of the current work task. The ergonomist asks the user to reach several postures involved in the task realization and propose via manikin B several recommendations;

Passive-active: Manikin A in motion replay and manikin B manipulated by the ergonomist. This mode is used for non direct evaluation of the current work task. The ergonomist replays a problematic sequence, indicates during the replay the problematic postures and propose recommendations.

The manikins are the main vector of the ergonomic information provided to the ergonomist as well as the main vector for the gesture recommendations provided to the main user. From the posture of manikins A and B, the software computes automatically the corresponding joint angles and the RULA and REBA (Rapid Entire Body Assessment) scores. The main user can visualize these scores through local and global colour codes associated to the manikin segments (from green to red). The ergonomist can also see these colour codes, but has additional tools enabling to tune the postural scores with adjustment (force, frequency,...) scores as proposed in the initial definition of both RULA and REBA scores. Additionally, the ergonomist can save/run sequences performed by the main user. At last additional outputs options are available. The ergonomist can activate/deactivate color codes, display the global scores on his screen, and display the kinematical traces (global scores, local scores, joint coordinates) on curves if necessary.

The ergonomist has also to be able to provide recommendations to the main user. At this point, the ergonomist can only modify directly the manikin B by clicking joints and displacing them in the environment. This interaction enables a simple recommendation metaphor, consisting in indicating the desired posture on manikin B with regard to the problematic one described on manikin A.

In the original paper, we just exhibited a sample trial with preliminary results on this interaction scheme.

End-user/design engineer interaction architecture

Second, the end-user and the design engineer need to communicate. The design engineer has to be able to show design constraints to the user, whereas the latter may have to indicate usability issues to the engineer. To this end, we developed several interaction tools and metaphors leading to, as well as for the ergonomist/end-user interaction, a set of design modes.

The design engineer can have different roles, depending on the operating mode currently being used during the session. According to figure 3.11. (a), the design engineer must be able to consider recommendations coming from the other users, and to act on the DMU to indicate and to proceed to modifications in accordance with the process specifications. In this operating mode, the design engineer has an active role as he is the only one allowed to modify the DMU. We can call this operating mode “direct design” mode. In this operating mode, the final user (and the ergonomist) use informative metaphors such as visual signals (arrows, spots, ...) and auditory signals (voice, bips...) to highlight process design issues. Moreover, the final user (and the ergonomist) must show reachable positions and volumes to the design engineer. At last, the design engineer must modify or move parts of the workstation with convenient manipulation techniques.

A second way to consider this interaction leads to the “supervised design mode” presented figure 3.11. (b). The design engineer is not acting directly on the DMU, but supervises, frames and validates regarding its process expertise the changes made by the other actors. Here, changes are directly realized regarding usability and ergonomic considerations, coming respectively from the final user’s experience and from the ergonomist’s analysis. The design engineer needs tools, such as process information metaphors, to frame and indicate to the other actors if the modifications they plan to do are compatible with the process specifications. Such information metaphors will mostly consist in plans and volumes materializations.

are materializing these limits. The 3D objects can be drawn in 3 different colors, manually chosen by the main user to indicate the kind of bound he is drawing - green = easy, yellow = difficult, red = ultimate.

In supervised design mode, the end-user deals directly with its own constraints, and the engineer must propose limits to the positions proposed by the user or by the ergonomist. For example, the user or the ergonomist can propose a new position for the the element of the workstation, while the engineer can express recommendations through other kinds of 3D annotations, expressing if the modification has a low, medium or high impact on the global design of the workstation. Here again, we have implemented some tools enabling an engineer to express these three different level impacts. The main metaphor used here is the one presented in figure 3.12. (a). It consists in the creation of translucent volumes with the same color-scale convention indicating the impact of the use of these bounds on the whole process. The engineer can use it during the user's interaction, and he can also create these bounds prior to the interaction of the user and the ergonomist in order to prepare the virtual environment.

To assess the usability of design modes and metaphors, we developed a use case and an experimental protocol presented below [151].

DESIGN MODES AND METAPHORS USABILITY FOR REACHABILITY ISSUES

The chosen use case is a very common ergonomic intervention: an element of the workstation is not optimally placed, and the final user needs to adopt uncomfortable postures to reach the element. Both ergonomist and final user request for a modification of the position of this element to the design engineer. Then all of the actors try to find a compromise between the user's comfort and the process specifications, which consists in finding an intersection $U \cap V$ between the reachable volume U defined by the final user (and maybe pondered by the ergonomist) and the volume defined by the design engineer with regard to the process specifications V . Figure 3.13. illustrates this use case. The use case has been implemented in the collaborative platform Collaviz [128], using its distribution features and its abilities for modelling the physical spaces of the users of CVE.

The experimentation did only involve the design engineer and the end-user. In order to assess the usability of the operating modes and metaphors between these actors, it was important to ensure that the results of the simulation were generic. Hence, in the experiment, each scene was unique but comparable with the others in terms of difficulty and of difference in morphology of the subjects. We assumed that a relevant indicator of difficulty could be extracted from the size and the shape of the reachable zone. Therefore, we created a difficulty criterion that was weighted volume of the intersection between U and V . The randomized parameters used to generate the scenes were the dead zones' positions, the end-user's position and the initial position of the DMU element. 2 levels of difficulty were tested: 1 and 2 dead zones (zones with process constraints).

Sixteen subjects (one woman and fifteen men) took part in this experiment (age: 24.8 ± 2.83 years old, height: 179 ± 8.54 cm).

The end-user was immersed in Immersia [150], which size was 9.60 m long, 3.10 m high and 2.88 m deep. They used a flystick device to drive a 3D cursor - an interaction tool to either grab and manipulate the DMU element in the supervised design mode or to draw reachable zones in the direct design mode. The design engineer had a simpler interface on a desktop computer with two windows that provided a top-view and a front-view of the CVE. We used a simplified avatar to represent the end-user's current activity in the design engineer field of view. The design engineer used a mouse to drive a 3D cursor to manipulate the DMU element in the direct design mode or to draw dead zones in the supervised design mode. The design engineer and the end-user were not allowed to use verbal communications because we wanted to evaluate the efficiency of the collaborative metaphors used to exchange information. We restricted to a single color the interaction metaphors designed above after a preliminary evaluation. Furthermore, the end-user used only one hand since they could represent

their reachable zone using only one interaction tool and the design engineer still could estimate their reachable limits. For each session, each subject was playing both roles (end-user and design engineer) to limit the number of experiments to run. In more details, 12 scenes (3 different scenes \times 2 levels of difficulty \times 2 operating modes) were randomly chosen from the pool of scenes related to a morphology category. The scenes were randomly ordered in each session in terms of level of difficulty and operating mode to be used. Once they had finished the first set of 12 scenes, they exchanged their roles and performed 12 new scenes chosen in accordance with the morphology category of the new end-user.

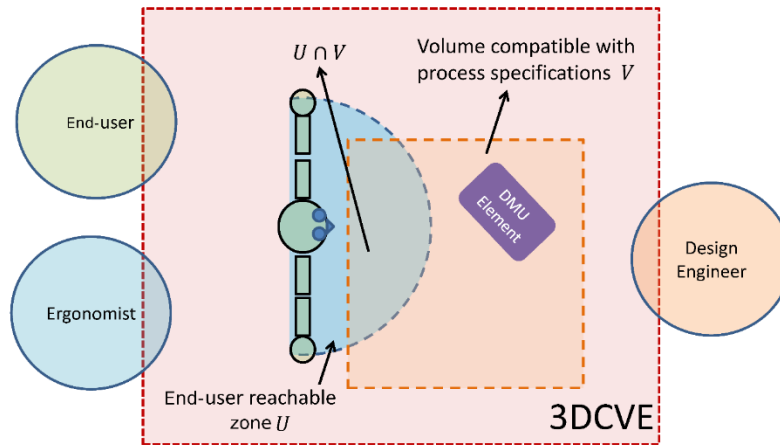


Figure 3.13. *A simple use-case illustrating reachability issues.*

To assess the usability of the system, in accordance with the ISO definition of usability [152], three main dimensions were investigated:

- **efficiency:** resources expended in relation to the accuracy and completeness of goals achieved. We assessed the efficiency by investigating the completion time per trial and the expected-final distance. The completion time was automatically recorded for the end-user and the design engineer to move the DMU element from its initial position to its final position and to validate the task. This metric is a direct indicator of the fastest operating mode to achieve the tasks. Then, the expected-final distance - the distance between the expected position of the DMU element on the table and its final position - was measured for each trial. The expected position was defined as the best trade-off between process and reachability constraints.
- **effectiveness:** accuracy and completeness with which specified users can achieve specified goals in particular environments. To assess the effectiveness, we computed the RULA score associated to the final position of the DMU element. It defines in terms of comfort the trade-off found by both users at the end of the design phase.
- **satisfaction:** comfort and acceptability of the work system to its users and other people affected by its use. To assess the satisfaction, we used 3 questionnaires: evaluation of the end-user's role and the respective collaborative metaphors; evaluation of the design engineer's role and the respective collaborative metaphors; and general comparison between two roles in the two operating design modes.

The statistical analysis of the results showed several interesting facts from this experimentation.

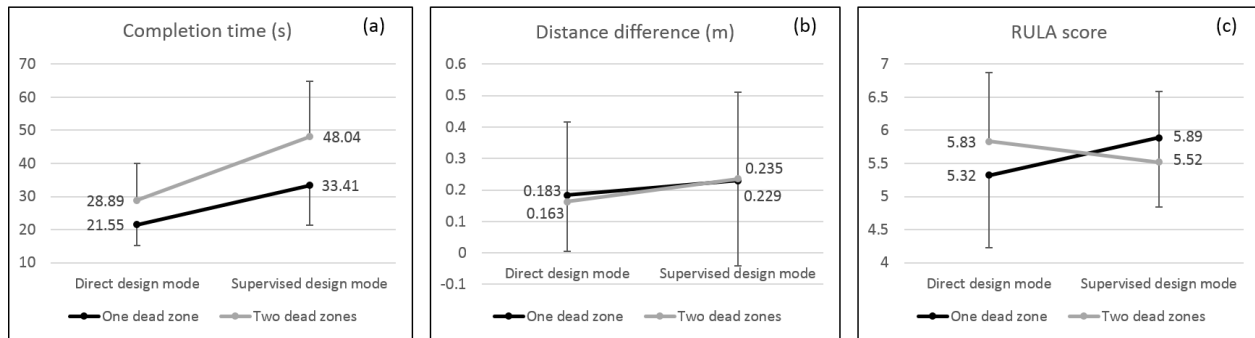


Figure 3.14. Interaction plots for usability metrics.

In summary, on the one hand, if we consider the efficiency as the most important dimension when the end-user and the design engineer work together in a workstation design process, the design engineer would be the one who should control the element. The reason is that they know the workstation design more specifically than the end-user. Moreover, in this case, the design engineer does not need to describe the workstation design specifications to the end-user. On the other hand, if we consider the effectiveness, i.e. the comfort of the end-user in the workstation design, as the main criterion to evaluate the usability of a design process, it would be better if the one who controls the element is the end-user. They have a real view of the workstation design from the first-person viewpoint and they can find a good spot to put the element regarding their own postural comfort. Moreover, we assume the result would have been significantly different with the addition of the ergonomist's role in the loop. Indeed, ergonomists have a knowledge about comfort, usability and activity enhancement that would have been of interest to criticize the trade-off found between the design engineer and the end-user and to maximize the effectiveness of the design session. The results of the subjective questionnaires make us think that users were satisfied of these tools to be used in a real design situation. However, having the feedback of expert users (design engineers in particular) seems mandatory in order to enhance the usability of the design tools.

CONCLUSION

The work presented in this part was finally a proof of concept. The experimentation presented above and the pilot trials proposed for the ergonomist features are far to be sufficient. Experimentations involving the 3 actors in more complex scenario would be a valuable validation of the concept. Moreover, the proposed use case did not ask to the design engineer to have any expertise. In more complex scenario, one may think that an understanding of the whole process and how the industrial machines work would be necessary to indicate any process constraint, further to reachability issues. Similarly, one may think that the DMU modification may only be done by the design engineer for much more complex DMUS with complex shapes and multiples components. In addition, understanding more in details how the interaction between actors is handled in such design sessions is a fundamental concept to enhance preventive ergonomics. Also, the experimentation proposed above was quite far from the standards we recommended in the biomechanical fidelity section. Task exertion assessment was not possible in this current implementation. This may imply a simulation of the envionring industrial process in order to make the user performing the work tasks in a much more realistic way. These issues are fundamental and may profit from recent developments of realistic industrial environments [153]. Last, we did not consider auditory communication in the implementation in order to challenge the metaphors. It seems obvious that in an operative setup, auditory communication should be authorized in addition to visual communication, as it can be found in several collaborative VR setups.

RELATED PUBLICATIONS:

- [Pontonnier et al. 2013]** Pontonnier, C., Duval, T., & Dumont, G. (2013). Sharing and bridging information in a collaborative virtual environment: application to ergonomics. In 2013 IEEE 4th International Conference on Cognitive Infocommunications (CogInfoCom), (pp. 121-126).
- [Pontonnier et al. 2014a]** Pontonnier, C., Dumont, G., Samani, A., Madeleine, P., & Badawi, M. (2014). Designing and evaluating a workstation in real and virtual environment: toward virtual reality based ergonomic design sessions. *Journal on Multimodal User Interfaces*, 8(2), 199-208.
- [Pontonnier et al. 2014b]** Pontonnier, C., Duval, T., & Dumont, G. (2014). Collaborative virtual environments for ergonomics: Embedding the design engineer role in the loop. In proceedings of IEEE International Workshop on Collaborative Virtual Environments (3DCVE), 2014 (pp. 1-5)
- [Nguyen et al. 2017]** Nguyen, H., Pontonnier, C., Hilt, S., Duval, T., & Dumont, G. (2017). VR-based operating modes and metaphors for collaborative ergonomic design of industrial workstations. *Journal on Multimodal User Interfaces*, 11(1), 97-111.

CONCLUSION

In conclusion, the work presented in this section was a first step in a relatively unexplored domain, dealing with the validity of VR for preventive ergonomics purposes. If we can find in several works recently published trying to deal with these issues, particularly by comparing real and virtual work situations [130,131,154,155], there are still a lot of room for additional developments, particularly in finding ways to assess complete tasks and complex interactions in VR.

Even if a proper VR-simulator involving the main actors of the design was found, improving the biomechanical fidelity to ensure a transferability of the results is still a goal to reach, particularly with the development of new display and interaction devices. Exploring the relevance of these devices (HMD, treadmills, tangible interfaces among others) for ergonomics is still to be done. Exploring these issues for much more complex tasks as well. These new devices are also of interest since their deployment cost is significantly lower than classical VR systems (cave, immersive rooms). With the objective to democratize the use of such setups, it seems mandatory to have a look at these systems for future preventive ergonomics development. All of this must be made in relation with the classical concepts developed to understand the human behavior in a virtual environment (avatar, presence, immersion...). Indeed, linking the biomechanical quantities to the cognitive and perceptive behavior of the user is fundamental to understand how we can link the results obtained in virtual environments to the real world.

Finally, collaborative environments may still lack of additional analysis tools, as the ones proposed in the first contribution chapter of this manuscript. Indeed, only postural scores were proposed here. Developing muscle-based or dynamics-based metrics is still to be done to enhance the decision support tools for ergonomists. The interaction between users and the deployment of such systems are still complex to run out of the academic scope, however we can see several initiatives of collaborative environments and media that may make this easier in the next years [156,157].

R

esearch perspectives

INTRODUCTION

The current manuscript summarizes 12 years of research in musculoskeletal simulation and virtual reality for ergonomics. This research has been largely driven by a wish of applicability to practical issues. I wished to consider the work context and the user as a central piece of my developments. In the following chapter, we will evoke some future research topics that seems fundamental to me considering the evolution of the industry and the place of the human inside it.

My main motivations remain the same: applying new methods and technologies to old but still prevalent issues. Objectivate physical risk factors and detect them early, with simple and quick methods.

EVOLVING INDUSTRIAL WORK CONDITIONS: 4.0 INDUSTRY

As we mentioned at the beginning of this report, the industry is now evolving concomitantly with new technologies (IoT, IA, robotics...). This evolution is commonly denoted as the “4.0 industry”, corresponding to the era of cyber-physical systems – systems in which computers and control entities autonomously control physical systems. 4.0 Industry is currently becoming real, with lots of new challenges to deal with. First, technological issues: smart production (producing in connection with the consumer), virtual prototyping, collaborative robotics, big data... Second, economic and social issues: environment, human at work, well-being... Finding the human place in these new productive environments is not straightforward. 4.0 industry tends to include the human into the cyber-physical system, by “augmenting” him in many ways. Therefore, each worker become a connected worker with more responsibilities and capacities, including being able to communicate with the production tools and performing news types of tasks.



Figure 4.1. Sample assistive devices currently proposed by companies in industrial context. On the left: the FORTIS passive exoskeleton, on the right: the JEAN PERROT Smart Glasses

4.0. Industry is an opportunity to consider the human place at work in a general way. This is an opportunity to consider health and well-being as a central dimension of this place. Moreover, the emergence of new technologies with connected and logged data is an asset for the evaluation of the work conditions, providing a lot of additional data to be processed and making possible longitudinal studies on large cohorts.

In this context, the emergence of assistive devices, making the worker more efficient, powerful and connected, is accompanied by several scientific questions to be solved. Among those (usability, acceptance ...), their impact on physical risk factors exposure is particularly important.

In my opinion, physical assistive devices (cobots, exoskeletons), supposed to minimize strenuous/repetitive tasks impact on the worker, must be validated in terms of physical risk factors reduction [158]. Indeed, these systems will impact the worker capacities to perform physical tasks, but compensatory strategies may appear. The motor control of the worker will be affected and may lead to other physical risk factors exposures, by changing the way work tasks are performed. Let us say that an exoskeleton manages to report the strength from the back to the legs, this force transfer will have short and long terms impact on worker exposure and health. At the same time, a cobot used to hold a heavy load will ask for accurate/stiff manipulations that may, at term, being malefic. A field able to provide answers to these questions is the musculoskeletal simulation. Therefore, there is a need of development of efficient musculoskeletal simulators able to evaluate the impact of the exoskeletons and cobots on the worker health, as well as to prototype them more efficiently.

At the same time, cognitive assistive devices (biofeedback devices, display devices, augmented reality devices, already used to assist several work tasks [164]) will also impact workers' health, since they will transform the way he works in many aspects. As reported in the literature [159], changes in cognition impacts the motor control associated to a task and alters it significantly, particularly in unfamiliar environments [129]. If this is true for virtual environments, augmented environments may as well provoke such changes. Altered perception may also lead to changes in the way the user perceives the task in terms of comfort. We noticed in previous works some compensatory processes related to altered perception [132,133], that may also appear in such connected/augmented environments.

Last, all of this must be easily assessed, in ecologic situations, with a minimal experimental deployment. This is in contradiction with the complexification of the models to be solved. Still, it asks for efficient methods (again) to be deployed, with affordable measurement devices, easy to use and deploy out of the lab.

In the following sections, I will develop the scientific ideas I want to explore regarding this context in the following years.

TOPIC 1: EVALUATING ASSISTIVE DEVICES AND THEIR IMPACT ON WORKERS HEALTH

From the context above, and in relation to the evolution of the human-machine interactions, I identified two major scientific issues that I want to explore in the few next years.

BIOMECHANICAL IMPACT OF PHYSICAL ASSISTIVE DEVICES

This first issue concerns the use of musculoskeletal models for the prototyping and the evaluation of exoskeletons. Indeed, there is a real potential in understanding how these devices impact the forces and motion of a subject. Musculoskeletal modeling and simulation are a real improvement in comparison with classical (EMG, mocap) motion analysis approaches, especially to explore compensatory muscle patterns that may arise in unexpected areas of the body when assisting it. A few preliminary studies already developed inverse dynamics-based methodologies proposing such approaches, without or with muscles, by integrating into the simulation the action of assistive devices. It has been done in several way, the simplest being adding external (simulated or measured) forces during the simulation resulting in altered internal forces [160]. Alternatively, some other

simulations integrated the mechanical structure of the exoskeleton inside the simulation and linked it to the model through mechanical joints [161]. There is a lot of room to enhance this interaction, particularly by integrating the control structure of the exoskeleton directly in the simulation if it is an active one, as well as using force-dependent kinematics features (and maybe deformable objects in a more general way) as it is done in [14] to develop passive exoskeletons such as [162]. Such applications ask for severe improvements in the simulation itself, particularly by handling closed loops systems that will appear systematically with such devices, and by adding co-simulation features to our developments enabling weak or strong coupling between rigid bodies simulation and deformable ones. A scheme summarizing the way such assessment can be done is given in figure 4.2. This is the solution scheme I proposed during my work as an expert in musculoskeletal simulation in the AFNOR group for the evaluation of the impact of assistive devices on workers in 2015-2017. I consider applying such methods soon since I have several industrial contacts wanting to compete their prototypes with objectives measures to enhance their performance. Additionally, I begin to supervise in 2019 a PhD student (Claire Livet, with Georges Dumont) working specifically on muscle forces estimation for closed loops systems, and a PhD student (Louise Demestre, with Nicolas Bideau, Guillaume Nicolas and Georges Dumont) working specifically on the coupling between musculoskeletal modeling and elastic structures simulation. Therefore, these two fundamental approaches in musculoskeletal modeling may strongly benefit to the approaches developed above. In addition to this, we are currently supervising (with Franck Multon and Georges Dumont) a PhD student (Olfa Haj Mahmoud) working specifically on continuous postural and force-based criteria, that are mandatory to assess the impact of an exoskeleton since dynamics of the worker during the task is clearly affected by such systems.

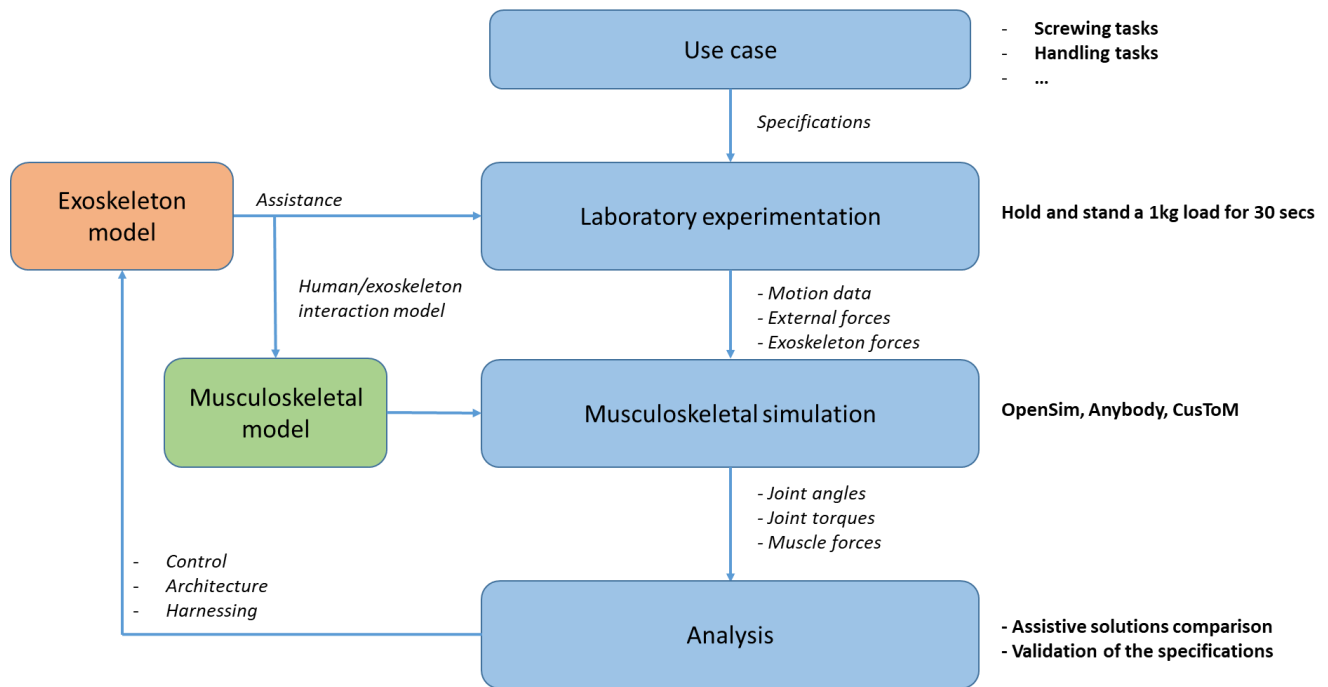


Figure 4.2. A numerical pipeline for the assessment of the biomechanical impact of an exoskeleton thanks to musculoskeletal simulation (issued from [2017]).

The scenario described above is applicable to the assessment of existing devices, but one can also consider applying such simulation for prototyping. Indeed, musculoskeletal simulation can be used in two ways in this context: first, by considering a virtual exoskeleton applied to a real or synthesized motion (the latter would be

in this case performed as an optimal control problem in direct dynamics), we can predict the effects of the control/architecture/harnessing on the forces and motion of a given subject. Second, prototyping of exoskeleton may ask for specifications relative to the population to assist (anthropometrics, physiological, force generation capacities), and relative to the task/motion to assist. Musculoskeletal simulation can be helpful in this context, by using database of models as a basis for population characterization. From these database, specific groups of individuals may be found to be representative for the development of a range of systems. This is the sense of what we made in Topic 2, chapter 2, and what we are currently exploring through the thesis of Pierre Puchaud. We explore the development of canonical models for prototyping, particularly by applying learning and classification methods (neural networks) effective for such data.

BIOMECHANICAL IMPACT OF COGNITIVE ASSISTIVE DEVICES

Following the issues evoked in introduction, the introduction in the work environment of more and more sophisticated cognitive assistive devices ask questions about their impact on workers health. This is part of a larger question being how human adapt its behavior to altered/augmented cognitive environments. Considering the work we previously conducted on biomechanical fidelity of virtual environments, I consider that the methodologies we developed to this end may be adapted for these new usage/devices evaluation.

Considering tasks that should be good candidates for cognitive assistance, i.e. assembly or maintenance tasks, we consider measuring, analyzing and comparing key biomechanical and efficiency factors associated to these tasks realized with the assistance (augmented) or not (non-augmented) of connected and augmented reality devices (tablets, AR glasses mostly). Scenarios can be tested through integrative measures realized in controlled environments. Measures could consist in EMG measures of the muscle activity and motion capture of the upper limb and neck/shoulder zone. Additional physiological measures (heart rate, gas exchange) could be added at some point to complete the assessment. Such assessments may result in metrics able to compare efficiency and risk factors regarding the assistive devices to be used and the types of task to be realized.

Following the methodology we developed for VR-based preventive ergonomics, we can propose in a second time interaction and visualization metaphors able to diminish the sensory-motor disturbance of connected and augmented reality devices with a similar level of efficiency.

I recently participated in the writing of an ITN particularly dedicated to these issues, led by Valentina Camomilla, and that should be resubmitted in December 2019. Therefore, I have several local and international contacts with companies designing AR devices, that may be interested by such assessments in a near future.

TOPIC 2: SIMPLIFYING THE EVALUATION

The complexification of the musculoskeletal models to be simulated leads to an increased computation time and an associated expertise of the software user. Since one of my major motivations in research lies in the development of affordable/easy-to-use/fast devices for ergonomics, such developments should be accompanied by the design of alternative methods enabling this fast and easy analysis. I see two major levers of simplification that are valuable research topics to be investigated. In both topics, the main idea resides in the usage of learning/classification techniques to get rid of complexity.

SIMPLIFYING THE CALIBRATION

As it has been explained in introduction of this manuscript, calibrating musculoskeletal models is a complex task to fulfill. A classical whole-body musculoskeletal model exhibits ~ 50 DoF, ~ 50 solids, and ~ 300 muscles that leads to ~ 5000 parameters to be known to fully calibrate it. At the geometrical level, the parameters are segment lengths, joint axes, joint locations and muscle paths mostly. At the inertial level, the parameters are the body segments inertial parameters (masses, centers of masses locations, inertia matrices). At the muscle level, the parameters are the force generation parameters (optimal muscle fiber length, maximal isometric force...). Individual factors such as height, weight, or fat mass index (macro parameters) are completing this model and may be used to scale it.

To simplify the calibration procedure, several ideas can be evoked.

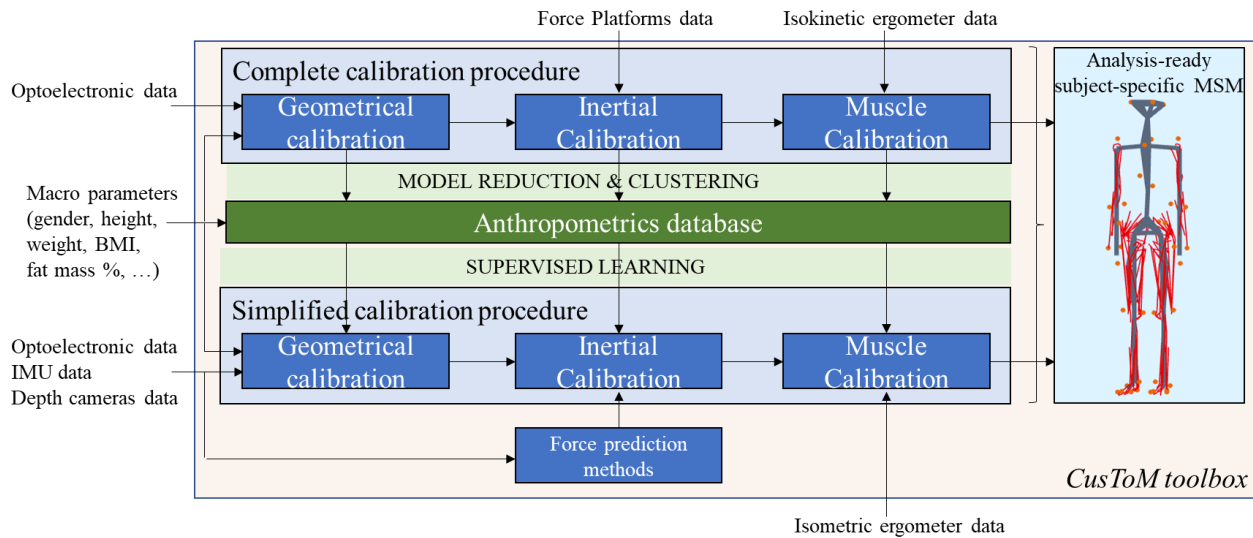


Figure 4.3. A simplification pipeline for musculoskeletal model scaling

First, we consider applying to a large cohort of subjects a “complete” calibration procedure enabling a sequential calibration of the 3 descriptive levels that are geometric, inertial (whole body model) and muscle (upper limbs and lower limbs flexion/extension joints, that are fundamental in ergonomics and sports applications), as it has been partly presented in chapter 2. To do so, an acquisition of reference motion capture data, reference external forces, and reference joint strengths data is necessary, in addition to the macro parameters. Some of these parameters can be linked to the MSM ones statistically.

Second, we consider finding an efficient low-dimensional representation of the inputs (particularly joint strengths) and outputs (MSM parameters) of the model that would lead to the reduction of parameters to optimize in the calibration. From this result, we consider training efficient interpolation rules to generate accurate initial guesses for the calibration methods using machine learning techniques (linear regression for example) and some of the macro parameters evoked above, leading to an anthropometrics-based calibration method. Finally, we consider using supervised learning (Neural networks or Autoencoders) to adapt the calibration to degraded/incomplete data captured with ‘out of the lab’ devices (dedicated isometric ergometer, IMU motion capture, Depth camera motion capture). To perform inverse dynamics, these dedicated devices

will ask for external forces prediction methods, consisting in finding a set of forces minimizing the “virtual forces” applied to the model, as presented in [101,107] and chapter 2, and implemented in CusToM.

Such developments are asking for large cohorts and experimental means. We already began to develop such protocols within the thesis of Pierre Puchaud and I am currently applying to national projects in order to develop this approach.

SIMPLIFYING THE FORCES ESTIMATION

We presented in the second chapter of this research summary the MusIC method (Muscle forces Interpolation and Correction). The MusIC method is based on two main hypotheses:

- the muscle forces problem can be first solved joint per joint and the inter-joint muscular coupling (multi-articular muscles) can be taken into account a posteriori;
- the muscle forces can be corrected to respect the dynamic equilibrium.

The method has been proved to be at least ten times faster at runtime than classical optimization for similar results in terms of optimality. This rapidity is of first importance because it allows the user (subject) to analyze her/his motion or gesture while performing it and so allows to learn how to improve this motion or gesture.

However, limitations remain:

- First, the method only applies to open-loop models, meaning that no complex architecture including kinematical loop can be used with the method;
- Second, the method asks for a database generation that can be time consuming. There is a need of simplification of the database;
- Third, the method is unable to consider muscle activation dynamics;
- Last, the database gives results based on the joint configuration only, whereas angular velocities must be considered since muscles are visco-elastic actuators.

Therefore, regarding the complexification of the models to solve, it is necessary to deploy methods able to provide accurately the muscle forces arising from constrained dynamics and efficient in terms of computation time, activation dynamics and actuation models.

Such a method can be developed with a similar philosophy to the one we proposed for the calibration and the original MusIC method. Indeed, results from an optimization can be learned from a database of results. It can be made from interpolation methods, as well as more advanced learning methods, as proposed at the end of the second chapter. I definitely think that such approaches are valuable, at the extent that we need to keep a physiological and biomechanical sense of the quantities to be computed.

Last, these methods can be only validated thanks to experimentations, enabling the comparison of the muscle forces estimation results with measures of the muscle activity (through EMG for example).

SIMPLIFYING THE MEASURE

All of these developments should be made with regard to new technologies that are more adapted to on field measure than classical motion analysis tools we can find in a laboratory. Alternative motion capture means are really appealing. It seems important to develop accurate and reliable methods able to provide joint angles, joint

torques and muscle forces from affordable and easy-to-deploy devices such as inertial measurement units or depth cameras (Kinect for example). Moreover, the measure of external forces is still an issue in on field measures. From this perspective, the methods presented above need to be adapted to incomplete, noisy data, with badly calibrated models. This means that the data should be completed or corrected at some point to deliver relevant results.

Again, this can be approached by model reduction and machine learning techniques. As we already showed in chapter 2, Kinect can be a reliable assessment tool for internal forces, at the condition that its initial measure is processed and corrected with a database. At the same time, external forces prediction methods are more and more efficient, and we participated to this enhancement quite largely with some major publications. We plan to continue exploring these new devices and see how we can complete their measure to obtain rich and reliable information from a degraded and incomplete data. We are currently testing optimal contact descriptions with regard to the subject and task specificities, that could lead to a better estimation of external forces from motion. Such development may be impactful for on-field ergonomics assessment in the following years.

SIMPLIFYING PREVENTION

The 3 propositions above are applicable to corrective ergonomics. However, we may consider also developing additional ideas to enable an easier preventive ergonomics application, following the work presented in chapter 3. Considering the growth of the virtual reality market, with more affordable display and interactive devices, there are several developments to be made in order to make them usable for ergonomics. We can assess the usage of such devices through the methodologies developed in the manuscript, particularly from the biomechanical fidelity point of view. Again, the idea is to find levers of simplifications able to make such minimal setups usable by anyone interested in for a reasonable cost and with a maximal accuracy.

TOPIC 3: INTEGRATING

Developing the topics evoked above will be of relevance if they can be easily applied through a relevant software, easy-to-use and asking no specific expertise in coding/computer science. From this philosophy, we developed the CusToM toolbox, presented in topic 4 of chapter 2. The topics proposed above will all find a natural place inside this software, reinforcing its efficiency and versatility. This is important since we have the ambition to make this software a major actor of the musculoskeletal simulation, following the success of developments such as OpenSim and Anybody. To this end, we proposed a public Git³ that is currently active with 4 main contributors (including me) and regular visitors, clones and downloads. The Git is active since less than 1 year and will be a central tool for many PhD students in the following years.

³ <https://github.com/anmuller/CusToM>

CONCLUSION

From the 3 topics proposed above, we can merge a more general concept: assessing workers health and well-being with regard of the evolution of the work conditions, particularly regarding the technology advances. This is clearly the project I want to push front in the next years to come. It is ambitious, challenging and a lot of work. But there is nothing that cannot be reached in these challenges. I really believe that these objectives are realistic and may found lots of final usage in the industry as well as in other domains such as sports sciences of clinics.

Some of the challenges proposed above are already at the heart of some of the projects I am currently participating to or leading, and some other will be developed in the next years. For sure, a real and important effort must be made to make these developments more in collaboration with companies. My feeling is that the last 2 years, I had many more industrial contacts than in the last 10 years. This is telling me that the companies are ready to hear how they can enhance the work conditions of their employees in synergy with their production /rentability objectives, much more than 10 years ago. This maturity is concomitant with the maturity of several research works we developed. I see a rapid growth of our research collaboration with the industry, and this is clearly good news about my objectives.

As a conclusion to this document, I would like to thank again all the people I worked with. As an associate professor, I clearly not have the time I would like to have to develop my research issues. Fortunately, I had the opportunity to supervise some amazing PhD students and post-doctoral fellows that made some amazing work on all the topics evoked in this summary. I hope that I will still be the case in the following years.

R

EFERENCES

- [1] 6th European Working Conditions Survey (2015), Eurofound
- [2] Sjøgaard, G., Sejersted, O. M., Winkel, J., Smolander, J., Jørgensen, K., & Westgaard, R. (1995). Exposure assessment and mechanisms of pathogenesis in work-related musculoskeletal disorders: Significant aspects in the documentation of risk factors. *Work & Health—scientific basis of progress in the working environment*, Brussels, The Health and Safety Directorate, Commission of the European Communities, 75-87.
- [3] Winkel, J., & Westgaard, R. (1992). Occupational and individual risk factors for shoulder-neck complaints: Part I—Guidelines for the practitioner. *International Journal of Industrial Ergonomics*, 10(1-2), 79-83.
- [4] McAtamney, L., & Corlett, E. N. (1993). RULA: a survey method for the investigation of work-related upper limb disorders. *Applied ergonomics*, 24(2), 91-99.
- [5] Hignett, S., & McAtamney, L. (2000). Rapid entire body assessment (REBA). *Applied ergonomics*, 31(2), 201-205.
- [6] Waters, T. R., Putz-Anderson, V., Garg, A., & Fine, L. J. (1993). Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics*, 36(7), 749-776.
- [7] Bertilsson, E., Högberg, D., & Hanson, L. (2010). Digital human model module and work process for considering anthropometric diversity. *Advances in Applied Digital Human Modeling*, 568-575.
- [8] Maurice, P., Padois, V., Measson, Y., & Bidaud, P. (2016). Experimental assessment of the quality of ergonomic indicators for dynamic systems computed using a digital human model.
- [9] Muller, A., Haering, D., Pontonnier, C., & Dumont, G. (2017). Non-invasive techniques for musculoskeletal model calibration. *Congrès Français de Mécanique*
- [10] Jayaram, U., Jayaram, S., Shaikh, I., Kim, Y., & Palmer, C. (2006). Introducing quantitative analysis methods into virtual environments for real-time and continuous ergonomic evaluations. *Computers in industry*, 57(3), 283-296.
- [11] Wang, Y., Liao, K. B., Guo, Y., Zhang, Y. Y., Zhang, W., & Wu, S. (2007). Development and application of integrated human machine interaction simulation system. *Journal of system simulation*, 19(11), 2492-2495.
- [12] Wilson, J. R. (1999). Virtual environments applications and applied ergonomics. *Applied Ergonomics*, 30(1), 3-9.
- [13] Pontonnier, C., Dumont, G., Samani, A., Madeleine, P., & Badawi, M. (2014). Designing and evaluating a workstation in real and virtual environment: toward virtual reality based ergonomic design sessions. *Journal on Multimodal User Interfaces*, 8(2), 199-208.
- [14] Damsgaard, M., Rasmussen, J., Christensen, S. T., Surma, E., & De Zee, M. (2006). Analysis of musculoskeletal systems in the AnyBody Modeling System. *Simulation Modelling Practice and Theory*, 14(8), 1100-1111.
- [15] Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., ... & Thelen, D. G. (2007). OpenSim: open-source software to create and analyze dynamic simulations of movement. *IEEE transactions on biomedical engineering*, 54(11), 1940-1950.

- [16] Lu, T. W., & O'Connor, J. J. (1999). Bone position estimation from skin marker co-ordinates using global optimisation with joint constraints. *Journal of biomechanics*, 32(2), 129-134.
- [17] Bonnet, V., Richard, V., Camomilla, V., Venture, G., Cappozzo, A., & Dumas, R. (2017). Joint kinematics estimation using a multi-body kinematics optimisation and an extended Kalman filter, and embedding a soft tissue artefact model. *Journal of biomechanics*, 62, 148-155.
- [18] Featherstone, R. (2014). *Rigid body dynamics algorithms*. Springer.
- [19] An, K. N., Kwak, B. M., Chao, E. Y., & Morrey, B. F. (1984). Determination of muscle and joint forces: a new technique to solve the indeterminate problem. *Journal of biomechanical engineering*, 106(4), 364-367.
- [20] Herzog, W. (1987). Individual muscle force estimations using a non-linear optimal design. *Journal of Neuroscience Methods*, 21(2-4), 167-179.
- [21] Merrill, Z., Perera, S., Chambers, A., & Cham, R. (2019). Age and Body Mass Index Associations with Body Segment Parameters. *Journal of Biomechanics*.
- [22] Yeadon, M. R. (1990). The simulation of aerial movement—II. A mathematical inertia model of the human body. *Journal of biomechanics*, 23(1).
- [23] De Leva, P. (1996). Adjustments to Zatsiorsky-Seluyanov's segment inertia parameters. *Journal of biomechanics*, 29(9).
- [24] Dumas, R., Cheze, L., & Verriest, J. P. (2007). Adjustments to McConville et al. and Young et al. body segment inertial parameters. *Journal of biomechanics*, 40(3), 543-553.
- [25] Pontonnier, C., De Zee, M., Samani, A., Dumont, G., & Madeleine, P. (2014). Strengths and limitations of a musculoskeletal model for an analysis of simulated meat cutting tasks. *Applied ergonomics*, 45(3), 592-600.
- [26] Modenese, L., Ceseracciu, E., Reggiani, M., & Lloyd, D. G. (2016). Estimation of musculotendon parameters for scaled and subject specific musculoskeletal models using an optimization technique. *Journal of biomechanics*, 49(2).
- [27] Jensen, R. K. (1978). Estimation of the biomechanical properties of three body types using a photogrammetric method. *Journal of biomechanics*, 11(8).
- [28] Pearsall, D. J., Reid, J. G., & Ross, R. (1994). Inertial properties of the human trunk of males determined from magnetic resonance imaging. *Annals of biomedical engineering*, 22(6).
- [29] Davidson, P. L., Wilson, S. J., Wilson, B. D., & Chalmers, D. J. (2008). Estimating subject-specific body segment parameters using a 3-dimensional modeller program. *Journal of biomechanics*, 41(16).
- [30] Muller, A., Germain, C., Pontonnier, C., & Dumont, G. (2016). A simple method to calibrate kinematical invariants: application to overhead throwing. *ISBS-Conference Proceedings Archive* (Vol. 33, No. 1).
- [31] Reinbolt, J. A., Schutte, J. F., Fregly, B. J., Koh, B. I., Haftka, R. T., George, A. D., & Mitchell, K. H. (2005). Determination of patient-specific multi-joint kinematic models through two-level optimization. *Journal of biomechanics*, 38(3).

- [32] Andersen, M. S., Damsgaard, M., MacWilliams, B., & Rasmussen, J. (2010). A computationally efficient optimisation-based method for parameter identification of kinematically determinate and over-determinate biomechanical systems. *Computer methods in biomechanics and biomedical engineering*, 13(2).
- [33] Lund, M. E., Andersen, M. S., de Zee, M., & Rasmussen, J. (2015). Scaling of musculoskeletal models from static and dynamic trials. *International Biomechanics*, 2(1).
- [34] Vaughan, C. L., Andrews, J. G., & Hay, J. G. (1982). Selection of body segment parameters by optimization methods. *Journal of biomechanical engineering*, 104(1).
- [35] Venture, G., Ayusawa, K., & Nakamura, Y. (2009). Identification of human mass properties from motion. *IFAC Proceedings Volumes*, 42(10).
- [36] Jovic, J., Escande, A., Ayusawa, K., Yoshida, E., Kheddar, A., & Venture, G. (2016). Humanoid and human inertia parameter identification using hierarchical optimization. *IEEE Transactions on Robotics*, 32(3).
- [37] Hansen, C., Venture, G., Rezzoug, N., Gorce, P., & Isableu, B. (2014). An individual and dynamic Body Segment Inertial Parameter validation method using ground reaction forces. *Journal of biomechanics*, 47(7).
- [38] Bonnet, V., & Venture, G. (2015). Fast determination of the planar body segment inertial parameters using affordable sensors. *IEEE Transactions on neural systems and rehabilitation engineering*, 23(4), 628-635.
- [39] Reinbolt, J. A., Haftka, R. T., Chmielewski, T. L., & Fregly, B. J. (2007). Are patient-specific joint and inertial parameters necessary for accurate inverse dynamics analyses of gait?. *IEEE transactions on biomedical engineering*, 54(5).
- [40] Zhao, J., Wei, Y., Xia, S., & Wang, Z. (2010, October). Estimating human body segment parameters using motion capture data. 2010 4th International Universal Communication Symposium (IUCS).
- [41] Pillet, H., Bonnet, X., Lavaste, F., & Skalli, W. (2010). Evaluation of force plate-less estimation of the trajectory of the centre of pressure during gait. Comparison of two anthropometric models. *Gait & posture*, 31(2).
- [42] Heinen, F., Lund, M. E., Rasmussen, J., & de Zee, M. (2016). Muscle–tendon unit scaling methods of Hill-type musculoskeletal models: An overview. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, 230(10).
- [43] Garner, B. A., & Pandy, M. G. (2003). Estimation of musculotendon properties in the human upper limb. *Annals of biomedical engineering*, 31(2).
- [44] Heinen, F., Sørensen, S. N., King, M., Lewis, M., de Zee, M., & Rasmussen, J. (2015). Prediction of muscle-tendon parameters based on isokinetic measurements. *Annual Meeting of the Danish Society of Biomechanics*.
- [45] de Monsabert, B. G., Rao, G., Gay, A., Berton, E., & Vigouroux, L. (2017). A scaling method to individualise muscle force capacities in musculoskeletal models of the hand and wrist using isometric strength measurements. *Medical & biological engineering & computing*, 55(12), 2227-2244.
- [46] Venture, G., Yamane, K., & Nakamura, Y. (2005, December). Identifying musculo-tendon parameters of human body based on the musculo-skeletal dynamics computation and hill-stroeve muscle model. 2005 5th IEEE-RAS International Conference on Humanoid Robots.

- [47] Murai, A., Kurosaki, K., Yamane, K., & Nakamura, Y. (2010). Musculoskeletal-see-through mirror: Computational modeling and algorithm for whole-body muscle activity visualization in real time. *Progress in biophysics and molecular biology*, 103(2-3), 310-317.
- [48] Van den Bogert, A. J., Geijtenbeek, T., Even-Zohar, O., Steenbrink, F., & Hardin, E. C. (2013). A real-time system for biomechanical analysis of human movement and muscle function. *Medical & biological engineering & computing*, 51(10), 1069-1077.
- [49] Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2017). Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis. *Medical & biological engineering & computing*, 55(4), 609-619.
- [50] Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2017). Accuracy and repeatability of single-pose calibration of inertial measurement units for whole-body motion analysis. *Gait & posture*, 54, 80-86.
- [51] Karatsidis, A., Jung, M., Schepers, H. M., Bellusci, G., de Zee, M., Veltink, P. H., & Andersen, M. S. (2018). Predicting kinetics using musculoskeletal modeling and inertial motion capture. *arXiv preprint arXiv:1801.01668*.
- [52] Karatsidis, A., Jung, M., Schepers, H. M., Bellusci, G., de Zee, M., Veltink, P. H., & Andersen, M. S. (2019). Musculoskeletal model-based inverse dynamic analysis under ambulatory conditions using inertial motion capture. *Medical engineering & physics*.
- [53] Plantard, P., Muller, A., Pontonnier, C., Dumont, G., Shum, H. P., & Multon, F. (2017). Inverse dynamics based on occlusion-resistant Kinect data: Is it usable for ergonomics?. *International Journal of Industrial Ergonomics*, 61.
- [54] Pontonnier, C., & Dumont, G. (2009). Inverse dynamics method using optimization techniques for the estimation of muscles forces involved in the elbow motion. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 3(4), 227.
- [55] Pontonnier, C., & Dumont, G. (2010). From motion capture to muscle forces in the human elbow aimed at improving the ergonomics of workstations. *Virtual and Physical prototyping*, 5(3), 113-122.
- [56] Muller, A., Pontonnier, C., & Dumont, G. (2018). The MusIC method: a fast and quasi-optimal solution to the muscle forces estimation problem. *Computer methods in biomechanics and biomedical engineering*, 21(2), 149-160.
- [57] Muller, A., Pontonnier, C., & Dumont, G. (2018). MusIC method enhancement by a sensitivity study of its performance: application to a lower limbs musculoskeletal model. *Computer Methods in Biomechanics and Biomedical Engineering*.
- [58] Vaughan, C. L., Andrews, J. G., & Hay, J. G. (1982). Selection of body segment parameters by optimization methods. *Journal of biomechanical engineering*, 104(1), 38-44.
- [59] Ojeda, J., Martínez-Reina, J., & Mayo, J. (2016). The effect of kinematic constraints in the inverse dynamics problem in biomechanics. *Multibody System Dynamics*, 37(3), 291-309.
- [60] Muller, A., Pontonnier, C., & Dumont, G. (2017). Uncertainty propagation in multibody human model dynamics. *Multibody System Dynamics*, 40(2), 177-192.

- [61] De Zee, M., Hansen, L., Wong, C., Rasmussen, J., & Simonsen, E. B. (2007). A generic detailed rigid-body lumbar spine model. *Journal of biomechanics*, 40(6), 1219-1227.
- [62] Van der Helm, F. C. (1994). A finite element musculoskeletal model of the shoulder mechanism. *Journal of biomechanics*, 27(5), 551-569.
- [63] Cheze, L., Fregly, B. J., & Dimnet, J. (1995). A solidification procedure to facilitate kinematic analyses based on video system data. *Journal of biomechanics*, 28(7), 879-884.
- [64] Dumas, R., Camomilla, V., Bonci, T., Cheze, L., & Cappozzo, A. (2014). Generalized mathematical representation of the soft tissue artefact. *Journal of biomechanics*, 47(2), 476-481.
- [65] Van Den Bogert, A. J., & Su, A. (2008). A weighted least squares method for inverse dynamic analysis. *Computer methods in biomechanics and biomedical engineering*, 11(1), 3-9.
- [66] Venture, G., Ayusawa, K., & Nakamura, Y. (2009, May). A numerical method for choosing motions with optimal excitation properties for identification of biped dynamics-an application to human. In 2009 IEEE International Conference on Robotics and Automation (pp. 1226-1231). IEEE.
- [67] Muller, A., Chauwin, M., Pontonnier, C., & Dumont, G. (2017, July). Influence of Physiological Constraints on a Subject-specific BSIP Calibration.
- [68] Hussain, S. J., & Frey-Law, L. (2016). 3D strength surfaces for ankle plantar-and dorsi-flexion in healthy adults: an isometric and isokinetic dynamometry study. *Journal of foot and ankle research*, 9(1), 43.
- [69] Yeadon, M. R., King, M. A., & Wilson, C. (2006). Modelling the maximum voluntary joint torque/angular velocity relationship in human movement. *Journal of biomechanics*, 39(3), 476-482.
- [70] Anderson, D. E., Madigan, M. L., & Nussbaum, M. A. (2007). Maximum voluntary joint torque as a function of joint angle and angular velocity: model development and application to the lower limb. *Journal of biomechanics*, 40(14), 3105-3113.
- [71] Hernandez, V., Rezzoug, N., Gorce, P., & Venture, G. (2018). Force feasible set prediction with artificial neural network and musculoskeletal model. *Computer methods in biomechanics and biomedical engineering*, 21(14), 740-749.
- [72] Bosco, C., Belli, A., Astrua, M., Tihanyi, J., Pozzo, R., Kellis, S., ... & Tranquilli, C. (1995). A dynamometer for evaluation of dynamic muscle work. *European journal of applied physiology and occupational physiology*, 70(5), 379-386.
- [73] Frey-Law, L. A., Laake, A., Avin, K. G., Heitsman, J., Marler, T., & Abdel-Malek, K. (2012). Knee and elbow 3D strength surfaces: peak torque-angle-velocity relationships. *Journal of applied biomechanics*, 28(6), 726-737.
- [74] Gülch, R. W. (1994). Force-velocity relations in human skeletal muscle. *International journal of sports medicine*, 15(S 1), S2-S10.
- [75] Brown, I. E., Scott, S. H., & Loeb, G. E. (1996). Mechanics of feline soleus: II Design and validation of a mathematical model. *Journal of Muscle Research & Cell Motility*, 17(2), 221-233.

- [76] van Soest, A. J., Huijling, P. A., & Solomonow, M. (1995). The effect of tendon on muscle force in dynamic isometric contractions: a simulation study. *Journal of biomechanics*, 28(7), 801-807.
- [77] Wickiewicz, T. L., Roy, R. R., Powell, P. L., Perrine, J. J., & Edgerton, V. R. (1984). Muscle architecture and force-velocity relationships in humans. *Journal of Applied Physiology*, 57(2), 435-443.
- [78] Looft, J. M., & Frey-Law, L. A. (2015). Modelling three-dimensional human strength capacity: logistic vs. polynomial surface equations. *International Journal of Human Factors Modelling and Simulation*, 5(1), 5-18.
- [79] Steven Moore, J., & Garg, A. (1995). The strain index: a proposed method to analyze jobs for risk of distal upper extremity disorders. *American Industrial Hygiene Association Journal*, 56(5), 443-458.
- [80] Haering, D., Pontonnier, C., Bideau, N., Nicolas, G., & Dumont, G. (2017, July). Task Specific Maximal Elbow Torque Model For Ergonomic Evaluation.
- [81] van den Bogert, A. J., Gerritsen, K. G., & Cole, G. K. (1998). Human muscle modelling from a user's perspective. *Journal of Electromyography and Kinesiology*, 8(2), 119-124.
- [82] Lloyd, D. G., & Besier, T. F. (2003). An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. *Journal of biomechanics*, 36(6), 765-776.
- [83] Hatze, H. (1977). A myocybernetic control model of skeletal muscle. *Biological cybernetics*, 25(2), 103-119.
- [84] Haering, D., Pontonnier, C., & Dumont, G. (2017). Which mathematical model best fit the maximal isometric torque-angle relationship of the elbow?.
- [85] Gauthier, A., Davenne, D., Martin, A., & Van Hoecke, J. (2001). Time of day effects on isometric and isokinetic torque developed during elbow flexion in humans. *European journal of applied physiology*, 84(3), 249-252.
- [86] Ellenbecker, T. S., & Roetert, E. P. (2003). Isokinetic profile of elbow flexion and extension strength in elite junior tennis players. *Journal of Orthopaedic & Sports Physical Therapy*, 33(2), 79-84.
- [87] Boone, D. C., & Azen, S. P. (1979). Normal range of motion of joints in male subjects. *JBJS*, 61(5), 756-759.
- [88] Hasan, Z., & Enoka, R. (1985). Isometric torque-angle relationship and movement-related activity. *Exp. Brain Res*, 59(3), 441-450.
- [89] Thomis, M. A., Van Leemputte, M., Maes, H. H., Blimkie, C. J., Claessens, A. L., Marchal, G., ... & Beunen, G. P. (1997). Multivariate genetic analysis of maximal isometric muscle force at different elbow angles. *Journal of Applied Physiology*, 82(3), 959-967.
- [90] Toji, H., & Kaneko, M. (2007). Effects of aging on force, velocity, and power in the elbow flexors of males. *Journal of physiological anthropology*, 26(6), 587-592.
- [91] Ma, R., Chablat, D., Bennis, F., & Ma, L. (2012). Human muscle fatigue model in dynamic motions. In *Latest Advances in Robot Kinematics* (pp. 349-356). Springer, Dordrecht.
- [92] Oksa, J., & Rintamäki, H. (1995). Dynamic work in cold. *Arctic medical research*, 54, 29-31.

- [93] Plantard, P., Shum, H. P., Le Pierres, A. S., & Multon, F. (2017). Validation of an ergonomic assessment method using Kinect data in real workplace conditions. *Applied ergonomics*, 65, 562-569.
- [94] Plantard, P., Shum, H. P., & Multon, F. (2017). Filtered pose graph for efficient kinect pose reconstruction. *Multimedia Tools and Applications*, 76(3), 4291-4312.
- [95] Wu, G., Van der Helm, F. C., Veeger, H. D., Makhous, M., Van Roy, P., Anglin, C., ... & Werner, F. W. (2005). ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: shoulder, elbow, wrist and hand. *Journal of biomechanics*, 38(5), 981-992.
- [96] Oh, S. E., Choi, A., & Mun, J. H. (2013). Prediction of ground reaction forces during gait based on kinematics and a neural network model. *Journal of biomechanics*, 46(14), 2372-2380.
- [97] Koopman, B., Grootenboer, H. J., & De Jongh, H. J. (1995). An inverse dynamics model for the analysis, reconstruction and prediction of bipedal walking. *Journal of biomechanics*, 28(11), 1369-1376.
- [98] Dijkstra, E. J., & Gutierrez-Farewik, E. M. (2015). Computation of ground reaction force using zero moment point. *Journal of biomechanics*, 48(14), 3776-3781.
- [99] Skals, S., Jung, M. K., Damsgaard, M., & Andersen, M. S. (2017). Prediction of ground reaction forces and moments during sports-related movements. *Multibody system dynamics*, 39(3), 175-195.
- [100] Fluit, R., Andersen, M. S., Kolk, S., Verdonchot, N., & Koopman, H. F. (2014). Prediction of ground reaction forces and moments during various activities of daily living. *Journal of biomechanics*, 47(10), 2321-2329.
- [101] Muller, A., Pontonnier, C., & Dumont, G. (2019). Motion-based prediction of hands and feet contact efforts during asymmetric handling tasks. *IEEE Transactions on Biomedical Engineering*.
- [102] Bonnet, V., Azevedo-Coste, C., Robert, T., Fraisse, P., & Venture, G. (2017). Optimal external wrench distribution during a multi-contact sit-to-stand task. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(7), 987-997.
- [103] Gagnon, D., Plamondon, A., & Larivière, C. (2018). A comparison of lumbar spine and muscle loading between male and female workers during box transfers. *Journal of biomechanics*, 81, 76-85.
- [104] Larivière, C., & Gagnon, D. (1998). Comparison between two dynamic methods to estimate triaxial net reaction moments at the L5/S1 joint during lifting. *Clinical Biomechanics*, 13(1), 36-47.
- [105] Plamondon, A., Gagnon, M., & Desjardins, P. (1996). Validation of two 3-D segment models to calculate the net reaction forces and moments at the L 5 S 1 joint in lifting. *Clinical Biomechanics*, 11(2), 101-110.
- [106] Kingma, I., de Looze, M. P., Toussaint, H. M., Klijnsma, H. G., & Bruijnen, T. B. (1996). Validation of a full body 3-D dynamic linked segment model. *Human Movement Science*, 15(6), 833-860.
- [107] Muller, A., Pontonnier, C., Robert-Lachaine, X., Dumont, G., & Plamondon, A. (2020). Motion-based prediction of external forces and moments and back loading during manual material handling tasks. *Applied ergonomics*, 82, 102935.

- [108] Pontonnier, C., Livet, C., Muller, A., Sorel, A., Dumont, G., & Bideau, N. (2019). Ground Reaction Forces and Moments Prediction of Challenging Motions: Fencing Lunges.
- [109] Erdemir, A., McLean, S., Herzog, W., & van den Bogert, A. J. (2007). Model-based estimation of muscle forces exerted during movements. *Clinical biomechanics*, 22(2), 131-154.
- [110] Muller, A., Pontonnier, C., Germain, C., & Dumont, G. (2015). Dealing with modularity of multibody models. *Computer methods in biomechanics and biomedical engineering*, 18(sup1), 2008-2009.
- [111] Barre, A., & Armand, S. (2014). Biomechanical ToolKit: Open-source framework to visualize and process biomechanical data. *Computer methods and programs in biomedicine*, 114(1), 80-87.
- [112] Moerman, K. M. (2018). GIBBON: The Geometry and Image-Based Bioengineering add-On. *J. Open Source Software*, 3(22), 506.
- [113] Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J. L., Hastie, T. J., & Delp, S. L. (2018). Machine learning in human movement biomechanics: best practices, common pitfalls, and new opportunities. *Journal of biomechanics*, 81, 1-11.
- [114] Koelewijn, A. D., Heinrich, D., & Van Den Bogert, A. J. (2019). Metabolic cost calculations of gait using musculoskeletal energy models, a comparison study. *BioRxiv*, 588590.
- [115] Stanev, D., & Moustakas, K. (2019). Stiffness modulation of redundant musculoskeletal systems. *Journal of biomechanics*, 85, 101-107.
- [116] Schiefer, C., Ellegast, R. P., Hermanns, I., Kraus, T., Ochsmann, E., Larue, C., & Plamondon, A. (2014). Optimization of inertial sensor-based motion capturing for magnetically distorted field applications. *Journal of biomechanical engineering*, 136(12), 121008.
- [117] Camomilla, V., Cereatti, A., Chêze, L., & Cappozzo, A. (2013). A hip joint kinematics driven model for the generation of realistic thigh soft tissue artefacts. *Journal of biomechanics*, 46(3), 625-630.
- [118] Cruz Ruiz, A. L., Pontonnier, C., Levy, J., & Dumont, G. (2017). A synergy-based control solution for overactuated characters: Application to throwing. *Computer Animation and Virtual Worlds*, 28(6), e1743.
- [119] Cruz Ruiz, A. L., Pontonnier, C., Pronost, N., & Dumont, G. (2017, September). Muscle-Based Control for Character Animation. In *Computer Graphics Forum* (Vol. 36, No. 6, pp. 122-147).
- [120] Cruz Ruiz, A. L., Pontonnier, C., & Dumont, G. (2017). Low-Dimensional Motor Control Representations in Throwing Motions. *Applied bionics and biomechanics*, 2017.
- [121] Noël, F., Roucoules, L., & Teissandier, D. (2005). Specification of product modelling concepts dedicated to information sharing in a collaborative design context. In *Advances in integrated design and manufacturing in mechanical engineering* (pp. 135-146). Springer, Dordrecht.
- [122] Sadeghi, M., Noël, F., & Hadj-Hamou, K. (2010). Development of control mechanisms to support coherency of product model during cooperative design process. *Journal of Intelligent Manufacturing*, 21(4), 539-554.
- [123] Duffy, V. G. (2007). A methodology for assessing industrial workstations using optical motion capture integrated with digital human models. *Occupational Ergonomics*, 7(1), 11-25.

- [124] Backstrand, G., Hogberg, D., De Vin, L. J., Case, K., & Piamonte, P. (2007). Ergonomics analysis in a virtual environment.
- [125] Whitman, L. E., Jorgensen, M., Hathiyari, K., & Malzahn, D. (2004, December). Virtual reality: its usefulness for ergonomic analysis. In Proceedings of the 36th conference on Winter simulation (pp. 1740-1745). Winter Simulation Conference.
- [126] Gerathewohl, S. J. (1969). Fidelity of simulation and transfer of training: a review of the problem (No. AM 69-24). Civil Aerospace Medical Institute.
- [127] Kopecki, A., Wossner, U., Mavrikios, D., Rentzos, L., Weidig, C., Roucoules, L., ... & Milecki, A. (2011). Visionair vision advanced infrastructure for research.
- [128] Dupont, F., Duval, T., Fleury, C., Forest, J., Gouranton, V., Lando, P., ... & Schmutz, A. (2010, October). Collaborative scientific visualization: the collaviz framework.
- [129] McMahan, R. P., Bowman, D. A., Zielinski, D. J., & Brady, R. B. (2012). Evaluating display fidelity and interaction fidelity in a virtual reality game. *IEEE transactions on visualization and computer graphics*, 18(4), 626-633.
- [130] Alexander, A. L., Brunyé, T., Sidman, J., & Weil, S. A. (2005). From gaming to training: A review of studies on fidelity, immersion, presence, and buy-in and their effects on transfer in pc-based simulations and games. *DARWARS Training Impact Group*, 5, 1-14.
- [131] Hu, B., Zhang, W., & Salvendy, G. (2012). Impact of multimodal feedback on simulated ergonomic measurements in a virtual environment: A case study with manufacturing workers. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 22(2), 145-155.
- [132] Hu, B., Ma, L., Zhang, W., Salvendy, G., Chablat, D., & Bennis, F. (2011). Can virtual reality predict body part discomfort and performance of people in realistic world for assembling tasks?. *arXiv preprint arXiv:1104.1191*.
- [133] Sanders, M. S., & McCormick, E. J. (1998). Human factors in engineering and design. *Industrial Robot: An International Journal*.
- [134] Pontonnier, C., Samani, A., Badawi, M., Madeleine, P., & Dumont, G. (2013). Assessing the ability of a vr-based assembly task simulation to evaluate physical risk factors. *IEEE transactions on visualization and computer graphics*, 20(5), 664-674.
- [135] Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015). Shoulder kinematics and spatial pattern of trapezius electromyographic activity in real and virtual environments. *PloS one*, 10(3), e0116211.
- [136] Samani, A., Pontonnier, C., Dumont, G., & Madeleine, P. (2015, August). Kinematic synergy in a real and a virtual simulated assembly task.
- [137] Burden, A. (2010). How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research. *Journal of electromyography and kinesiology*, 20(6), 1023-1035.
- [138] Borg, G. (1998). Borg's perceived exertion and pain scales. *Human kinetics*.

- [139] Kee, D., & Lee, I. (2012). Relationships between subjective and objective measures in assessing postural stresses. *Applied Ergonomics*, 43(2), 277-282.
- [140] Mathiassen, S. E., Nordander, C., Svendsen, S. W., Wellman, H. M., & Dempsey, P. G. (2005). Task-based estimation of mechanical job exposure in occupational groups. *Scandinavian journal of work, environment & health*, 31(2), 138-151.
- [141] Mathiassen, S. E. (2006). Diversity and variation in biomechanical exposure: what is it, and why would we like to know?. *Applied ergonomics*, 37(4), 419-427.
- [142] Jeong, J., Gore, J. C., & Peterson, B. S. (2001). Mutual information analysis of the EEG in patients with Alzheimer's disease. *Clinical neurophysiology*, 112(5), 827-835.
- [143] Bar-Yam, Y. (2004). A mathematical theory of strong emergence using multiscale variety. *Complexity*, 9(6), 15-24.
- [144] Svendsen, S. W., Mathiassen, S. E., & Bonde, J. P. (2005). Task based exposure assessment in ergonomic epidemiology: a study of upper arm elevation in the jobs of machinists, car mechanics, and house painters. *Occupational and environmental medicine*, 62(1), 18-27.
- [145] Scholz, J. P., & Schöner, G. (1999). The uncontrolled manifold concept: identifying control variables for a functional task. *Experimental brain research*, 126(3), 289-306.
- [146] Carlton, L. G. (1981). Processing visual feedback information for movement control. *Journal of Experimental Psychology: Human Perception and Performance*, 7(5), 1019.
- [147] Hilt, S., Pontonnier, C., & Dumont, G. (2017, December). Model Based Compensation for Low Mass Objects Haptic Manipulation in Virtual Environments. In *International Conference on Virtual Reality and Augmented Reality* (pp. 87-101). Springer, Cham.
- [148] Pontonnier, C., Duval, T., & Dumont, G. (2013, December). Sharing and bridging information in a collaborative virtual environment: application to ergonomics. In *2013 IEEE 4th International Conference on Cognitive Infocommunications (CogInfoCom)* (pp. 121-126). IEEE.
- [149] Pontonnier, C., Duval, T., & Dumont, G. (2014, March). Collaborative virtual environments for ergonomics: Embedding the design engineer role in the loop. In *2014 International Workshop on Collaborative Virtual Environments (3DCVE)* (pp. 1-5). IEEE.
- [150] Gaugne, R., Dumont, G., Gouranton, V., Chauffaut, A., & Arnaldi, B. (2012, June). Infrastructures immersives ouvertes dans le cadre du projet européen Visionair, exemple de la plateforme Immersia.
- [151] Nguyen, H., Pontonnier, C., Hilt, S., Duval, T., & Dumont, G. (2017). VR-based operating modes and metaphors for collaborative ergonomic design of industrial workstations. *Journal on Multimodal User Interfaces*, 11(1), 97-111.
- [152] ISO. 9241 (2015). ergonomics of human-system interaction - part 11 : Usability : Definitions and concepts
- [153] Schiavullo, R. (2019). Automotive and Transportation real-time rendering revolution by Unity3D High Definition Render Pipeline. *Virtual Reality*, 17, 05.

- [154] Rizzuto, M. A., Sonne, M. W., Vignais, N., & Keir, P. J. (2019). Evaluation of a virtual reality head mounted display as a tool for posture assessment in digital human modelling software. *Applied ergonomics*, 79, 1-8.
- [155] Lin, C. J., Abreham, B. T., & Woldegiorgis, B. H. (2019). Effects of displays on a direct reaching task: A comparative study of head mounted display and stereoscopic widescreen display. *International Journal of Industrial Ergonomics*, 72, 372-379.
- [156] Oyekan, J. O., Hutabarat, W., Tiwari, A., Grech, R., Aung, M. H., Mariani, M. P., ... & Dupuis, C. (2019). The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans. *Robotics and Computer-Integrated Manufacturing*, 55, 41-54.
- [157] Costa, A., Thomann, G., & Noël, F. (2019). Interactive technologies facilitating collaboration between projectists and non-projectists: A laboratory design experience. *Procedia CIRP*, 84, 55-60.
- [158] Bostelman, R., Li-Baboud, Y. S., Virts, A., Yoon, S., & Shah, M. (2019, March). Towards Standard Exoskeleton Test Methods for Load Handling. In *2019 Wearable Robotics Association Conference (WearRAcon)* (pp. 21-27). IEEE.
- [159] Stoffregen, T. A., Bardy, B. G., Smart, L. J., & Pagulayan, R. J. (2003). On the nature and evaluation of fidelity in virtual environments. *Virtual and adaptive environments: Applications, implications, and human performance issues*, 111-128.
- [160] Agarwal, P., Narayanan, M. S., Lee, L. F., Mendel, F., & Krovi, V. N. (2011, March). Simulation-based design of exoskeletons using musculoskeletal analysis. In *ASME 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. 1357-1364). American Society of Mechanical Engineers Digital Collection.
- [161] Ferrati, F., Bortoletto, R., & Pagello, E. (2013, July). Virtual modelling of a real exoskeleton constrained to a human musculoskeletal model. In *Conference on Biomimetic and Biohybrid Systems* (pp. 96-107). Springer, Berlin, Heidelberg.
- [162] Bosch, T., van Eck, J., Knitel, K., & de Looze, M. (2016). The effects of a passive exoskeleton on muscle activity, discomfort and endurance time in forward bending work. *Applied ergonomics*, 54, 212-217.
- [163] AFNOR AC Z 68-800 (2017) « Dispositifs d'assistance physique à contention de type exosquelettes robotisés ou non – Outils et repères méthodologiques pour l'évaluation de l'interaction humain-dispositif »...
- [164] Fraga-Lamas, P., Fernández-Caramés, T. M., Blanco-Novoa, Ó., & Vilar-Montesinos, M. A. (2018). A review on industrial augmented reality systems for the industry 4.0 shipyard. *IEEE Access*, 6, 13358-13375.